Managing Uncertainties in ICT Services Life Cycle Assessment using Fuzzy Logic

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***Abstract*—The deluge of new software services we are facing is associated with an expansion of supporting infrastructures, including networks and data centers, and a rapid renewal of end-user devices. However, this surge is accompanied by significant environmental impacts and encompassing factors, such as CO2e emissions or the depletion of rare metals and minerals. Given systems' complexity and rapid evolution, the ICT domain still struggles to understand its environmental impact and lacks openly available data to facilitate such assessments. Indeed, to the best of our knowledge, environmental impact assessments of ICT services have to deal with high margins of errors, which are insufficiently quantified and documented, yet wield a significant influence on the final estimation outcome. This paper, therefore, introduces an approach leveraging fuzzy logic to model and propagate uncertainties from the reference impact through the computations to the final results, encouraging their consideration by stakeholders. Adhering to the established 3-tier architecture used to conduct ICT services *Life Cycle Assessments* (LCA), we outline how assumptions can be mapped to fuzzy sets. We conclude with an illustrative example demonstrating the propagation of uncertainties throughout the environmental impact modeling process.**

***Index Terms*—Data Quality Indicator, Fuzzy Logic, Life Cycle Assessment, Life Cycle Inventory, Uncertainty**

I. INTRODUCTION

Software services are a keystone of our society, serving a wide range of purposes, from productivity to entertainment, and from online shopping to controlling connected devices. Due to their intangible nature, their environmental impact could be dismissed, or reduced to their share of power usage on end-user devices. Nonetheless, such a limited assessment methodology may conceal a large part of their impacts [1]. Indeed, modern software executed on end-user devices depends on network connectivity and interacts with multiple servers hosted in data centers across the world. Consequently, the environmental impact of such infrastructures must also be accounted for when assessing the environmental impact of software.

Furthermore, an exhaustive assessment of software impacts must account for the complete life cycle of the hardware entities involved in its usage. Indeed, as devices have a limited lifespan, a share of the impact of the device manufacturing impact can be imputed to the software under review. This is particularly relevant for battery-powered devices, as the power usage of software directly affects the lifespan of their battery. In particular, 37% of users declare that they did not attempt to repair their device when a failure occurred, including battery failures [2]. In such situation, the whole device would be replaced instead of the battery, further increasing environmental impacts. This imputation of manufacturing impacts on the usage extends to network and back-end infrastructures.

Assessing the impacts stemming from the usage and manufacturing of end-user devices, network, and back-end infrastructures, and subsequently allocating them to a given software remains a challenging endeavor. These impacts can only be estimated and thus not empirically validated, and the existing estimations in the state-of-the-art can vary significantly. *Life Cycle Assessment* (LCA) of ICT services heavily rely on such estimations, coupled with a set of hypotheses regarding the usage of software and impacts of underlying infrastructures. Consequently, the outcomes of such analyses represent broad estimates associated with high uncertainty, potentially overlooking the assessment of this uncertainty. Therefore, we believe that there is a need for a more systematic uncertainty management method in ICT services environmental LCA. This paper thus investigates novel approaches to estimate the impact of such services while systematically accounting for uncertainty.

RQ1: How to manage the uncertainty caused by diversity in sources of secondary data? LCAs depends on *Life Cycle Inventory* (LCI) databases as sources of secondary data, housing reference environmental impact factors for diverse resource types. In the rapidly evolving ICT sector, they are often unavailable, necessitating substitutions. Furthermore, multiple sources have to be combined for ICT services, which have various levels of quality and may diverge in their estimations. Therefore, there is a need for an uncertainty management method accounting for variations in estimations and their respective quality.

RQ2: How to allocate devices and infrastructure life cycle impacts to a software functional unit, while tracking and propagating the uncertainty of modeling hypotheses? Beyond tracking the energy consumed by software from the perspective of end-user's device, we aim to capture the broader impact of a functional unit implemented by a given software. We, therefore, need an appropriate methodology to compute resulting end-to-end impacts by considering the uncertainty introduced by sources of secondary data and modeling hypotheses.

In the remainder of this paper, Section II introduces the related work. Section III presents a solution to the management of secondary data quality and uncertainty, and Section IV introduces a novel impact estimation methodology to assesses the environmental impact of a software functional unit, relying on this quality and uncertainty management. Section V is an application of the proposed hypothesis on a use-case. Section VI discusses this approach and its limitations, and Section VII concludes this paper.

II. Related Work

Life Cycle Assessment (LCA) is a method defined in ISO 14040 [3] and 14044 [4] to assess the potential environmental impacts of a product or service over its whole life cycle—*i.e.*, from raw material acquisition to waste management via production and use phases. By using a systematic overview and perspective, LCA helps in identifying the shifting of a potential environmental burden between life cycle stages or individual processes [5]. All analyses conducted in an LCA are performed for a specific functional unit, which is a quantitative measure of the functions provided by the product or service [4], and allows for comparing systems sharing the same functional unit from an environmental perspective.

To complement the ISO 14040 [3] and 14044 [4] for the ICT sector, the ITU L.1410 [6] recommendation proposes a *Methodology for environmental life cycle assessments of information and communication technology goods, networks and services*. In the specific context of ICT services, a 3-tier architecture can be considered—encompassing end-user devices, networks, and data centers. Using a life cycle approach is crucial for ICT goods and services, as their embodied impact can be significantly larger than their usage impact [7]. However, it is important to note that, while an LCA will disclose direct environmental effects, it does not capture the broader role of ICT as an enabling technology [8].

Estimating and collecting accurate data has proven to be a challenging task within the ICT sector, due to its vast size, complexity, and variability [9], [10], [11], [12]. Consequently, the ecosystem lacks data regarding the environmental impact of the resources it consumes [13]. Moreover LCI databases—which serve as reference data for conducting LCA—are mostly closed-source, hindering the objective of transparent and reproducible research [14]. When openly available, scope and system boundaries are not always explicitly stated and similar to other studies [9], which hinders meaningful comparisons.

In such a rapidly evolving sector, environmental footprint estimations frequently rely on old and outdated reference data from LCI databases, leading to high inaccuracies within the results [15]. As demonstrated by Hischier *et al.* [16], assumptions made at the data inventory level significantly influence the outcomes. Indeed, the use of secondary data can pose a risk of derived errors, especially when considering generic data instead of specific one [17].

Arushanyan *et al.* [18] notably emphasize that rapid technological development constitutes a substantial source of variability in LCA results, affecting all ICT products and services life cycle. They identify another source of variability arising from the assumptions and hypotheses made during the modeling process. Furthermore, the authors consider one of the key challenges in ICT-related LCA as the documentation of these assumptions and modeling hypotheses.

While ICT-related LCA is associated with high levels of uncertainties, the uncertainty of results is rarely quantified [15], [19]. To tackle these limitations, Hischier *et al.* [16] proposes a systematic sensitivity analysis as a solution. Unfortunately, such extensive analyses are time-consuming due to the large data flows to handle.

The handling of uncertainties in LCAs is not limited to the ICT sector. Indeed, the result interpretation phase in LCA is particularly critical and can become subjective and time-consuming. One common approach to propagate uncertainties in LCA is the Monte Carlo method [20]. However, it requires a high number of simulations, resulting in a high calculation time [21]. To improve the clarity of interpretation, fuzzy sets have been proposed and adopted as means to quantify and propagate imprecision and uncertainties within various LCA steps [22], [23], [24]. However, despite being promising, fuzzy logic is not yet implemented in LCA software [21]. To the best of our knowledge, such methodology has not yet been used within ICT-related LCAs, a field involving particularly high uncertainties.

III. Quality & Uncertainty Management

In this paper, we leverage *data quality indicators* (DQI) to assess the relevance of its sources of secondary data and fuzzy logic to capture and propagate uncertainties within ICT-related LCA. This section overviews DQI and fuzzy logic.

A. Defining Data Quality Indicators

As stated in Section II, ICT-related environmental assessments encounter significant inaccuracies stemming from reference data sources. Such sources, referred to as *LCI secondary data* in LCA terminology, may report diverging estimates for the same variable and do not have a consistent quality. A large variety of sources representing the state of the art must be accounted for, but their relative weight within the results should be different depending on their quality. To quantify this quality, each LCI source is assessed with a DQI, following the method introduced by Weidema *et al.* [25]. Specifically, the DQI of a source covers 3 key aspects: *reliability*, *temporality*, and *technological correlation*. The Technological *correlation* highlights the similarity between the variable assessed by the source and the variable to model. For instance, when assessing the efficiency of a smartphone charger, studies regarding smartphone chargers have a higher technological correlation than studies focusing on laptop chargers. The *temporality* assesses the obsolescence of the source: older sources are deemed less representative than newer ones. For instance, a source published within the last 3 years is considered very recent, while a source published over 9 years ago is considered highly obsolete. Such obsolescence is caused by both the

TABLE I
THE CRITERIA TO ASSESS THE DQI OF A SOURCE

Score	Correlation	Temporality	Reliability
1	Not representative of the regarded variable	>10 years	Expert opinion
2	Representative of a similar variable	<10 years	Peer-reviewed expert opinion
3	Representative of the regarded variable	<6 years	Manufacturer data
4	Highly representative of the regarded variable	<3 years	Peer-review manufacturer data

improvements of estimation methods, as well as changes in the manufacturing and production methods over time. Finally, the *reliability* reflects the level of confidence placed in the provenance of the source. A peer-reviewed source authored by the device manufacturer is assigned the highest reliability, while a non-peer-reviewed expert opinion has the lowest one.

In contrast to Weidema *et al.* [25], *geographical correlation* is not accounted for, as most of the ICT hardware is produced within a limited geographical area. The *completeness* parameter is also omitted, as its purpose is to account for the limitations of sampling methods, which is not relevant in the LCA of ICT devices. Indeed, LCA focuses on a given subject, and results are not expected to vary between instances of this subject. Moreover, our DQI scores rely on 4 possible values per indicator, instead of the 5 provided by [25]. Indeed, some levels of quality do not apply to ICT assessment in technological correlation and reliability, while temporality criterion is made stricter to fit such a scale. Finally, the scale is reverted—a higher DQI indicates a higher quality—so that DQIs can be used as coefficients when aggregating a collection of sources. Hence, each category is assessed on a scale ranging from 1 to 4, and the overall data source DQI is computed as the sum of these individual scores. Table I maps the possible values for each category to the corresponding quality indicator. The total DQI of a source can thus vary between 3 and 12. For instance, a source that is representative of the variable, published by the manufacturer and peer-reviewed, but published more than 10 years ago gives a total DQI of 9.

B. Propagating Impact Factors Uncertainty

Different secondary sources can yield significantly varying results for the same device. For instance, manufacturers reports embodied impact of a smartphone such as 33, 57, or 94 kgCO2e [26], [27], [28]. Such variations can be caused by divergences in the manufacturing process, or in the LCA methodology. They can significantly influence the final estimated impacts, and should be propagated within all computations to be exposed in the final estimation. While multiple sources should be considered to capture a more comprehensive reference impact, averaging these values can lead to errors. Extreme values are not inherently incorrect and would not be captured by an average value. Thus, each source should be weighted by their respective DQI, presented in Section III-A, as they do not have consistent quality.

To address this constraint, we build on fuzzy logic, following the methodology introduced in [29]. In fuzzy logic, variables are not defined by a strict value in $\mathbb{R}$, but rather by a function $\mu_s : \mathbb{R} \rightarrow 0..1$ capturing the degree of membership of a value with a given fuzzy set s. A membership degree of 1 indicates the certainty that a value of x is possible, whereas a membership degree of 0 reflects that the fuzzy sets does not cover this value. Given this definition, two *crisp sets* are of interest: the *core* capture the range of values with the highest possibility of being correct, while the *support* represents the values with a non-null membership degree.

A fuzzy number is a special case of a fuzzy set that is convex, normalized, and defined in $\mathbb{R}$ as a piecewise continuous membership function. As such, they act as fuzzy intervals. This paper only considers *Trapezoidal Fuzzy Numbers* (TFN) as they allow for a compromise between the complexity and precision of calculations. For fuzzy numbers with a membership function defined as a trapezoidal shape, the *support* is wider than the *core* and both are crisp intervals. As such, the *core* is the interval $[m_L, m_R]$, and the *support* ranges in $[L, R]$, hence resulting in the TFN fuzzy set $< L, m_L, m_R, R >$. Then, Weckenmann *et al.* computes the TFN for any set of sampled points with Equations 1–4, with $\overline{x}$ representing the weighted average of the sampled variable, and C_v the coefficient of variation [29] .

$$m_L = \frac{\overline{x}}{1 + (0.5 \times C_v)} \tag{1}$$

$$m_R = \overline{x} \times (1 + (0.5 \times C_v)) \tag{2}$$

$$L = m_L - \overline{x} \times (\frac{1}{1 + (0.5 \times C_v)} - \frac{1}{1 + (2.5 \times C_v)}) \tag{3}$$

$$R = m_R - (\overline{x} \times 2 \times C_v) \tag{4}$$

To illustrate such intervals, Figure 1 depicts the TFN capturing the embodied impact of a smartphone. To account for quality variations in secondary sources, the main vertical axis is the DQI of each estimated impact in the aggregated secondary sources. Then, weighted secondary sources are converted to a TFN, visible is on the secondary vertical axis, with a *support* ranging from 31 to 102 kgCO2e, and a *core* between 48 and 65 kgCO2e. Therefore, $\overline{x}$ and C_v account for both variations in sources regarding a variable, but also variations in quality. While various data distributions may be reported in practice, due to the lack of samples available, we assume that any variable we consider is expected to follow a normal distribution over a large enough set of secondary sources. This assumption reflects the convergence of estimation and assess the relevance of TFN as an appropriate structure for capturing uncertainty of estimations at large.

Fuzzy logic supports arithmetic operations between fuzzy sets—*i.e.*, additions, subtractions, divisions, and multiplications. For instance, the sum of the sets $[a_1, a_2, a_3, a_4]$ and

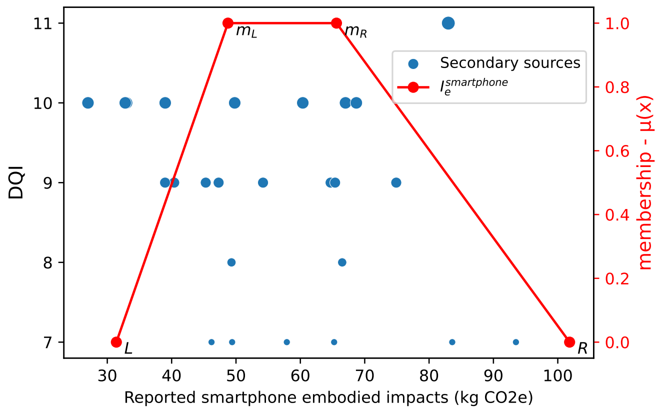

Fig. 1. Building the embodied impact factor of a smartphone, $I_e^{smartphone}$, as a TFN inferred from 24 secondary sources weighted by their DQI.

$[b_1, b_2, b_3, b_4]$ is $[a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4]$. Subtractions and multiplications apply similarly, while in divisions, the divisor is reverted—*i.e.*, $[a_1/b_4, a_2/b_3, a_3/b_2, a_4/b_1]$ [30]. Furthermore, any number $x \in \mathbb{R}$ can be converted to the fuzzy set $[x, x, x, x]$ to mix real numbers and fuzzy sets. Thus, the result of an equation containing fuzzy sets is a fuzzy set [31].

Since a fuzzy set contains both the value and the uncertainty of any hypothesis, arithmetic operations propagate uncertainty throughout all steps. The results convey all the possible estimations and uncertainties and, therefore, environmental assessments performed with fuzzy logic do not require to define scenarios, such as best or worst-case scenarios, or time-costly simulations that need additional hypotheses.

> **RQ1:** The quality of bibliographic sources can be assessed using DQI dimensions to score their reliability, temporality, and technological correlation. Multiple sources are then aggregated with fuzzy logic to capture more representative estimates of the state-of-the-art, where each variable is represented as a fuzzy set accounting for variations in sources and their respective quality. These fuzzy sets can be further used to systematically propagate uncertainty along all computation steps.

IV. Uncertainty-aware Impact Models

Following LCA methodology to estimate the environmental impact of software services, such as mobile apps and websites, the analysis is carried out for a defined *functional unit* [4]. The functional unit provides a reference to which inputs (data collected) and outputs (environmental impacts) are related or normalized [6]. Consequently, data collection involves a realistic user journey—*i.e.*, a sequence of actions on the application capturing the usage patterns on the reviewed functional unit. To more accurately capture uncertainties in properties beyond software measures, such as intrinsic network impacts, each of such properties is represented as a fuzzy set constructed, either from estimations drawn from a collection of sources, such as industrial reports, scientific publications, LCI databases, or from measured energy and data usage. Ultimately, the impact assessment phase—where inventory data is translated into an environmental impact [4]—employs the reference data source fuzzy sets and DQI detailed in Section III.

In the following, we adopt a 3-tier architecture—covering end-user devices, networks, and back-ends (cf. Section II)—to estimate the environmental footprint of ICT services. For each of these tiers, hypotheses and their associated uncertainties are proposed to conduct estimations without requiring extensive knowledge of their technical layout. For a given functional unit capturing a user journey, the analysis covers the application usage on the user's device, the network usage resulting from data transfers during the user journey, and the usage of remote servers to process and store such data. The impacts of these 3 layers are estimated from 3 separate components, and the total impact generated by the user journey under review is thus computed as their sum.

As highlighted in Section II, the embodied impacts of ICT devices—arising from manufacturing, raw materials extraction, transport, end of life—can surpass their usage impacts. Consequently, both the embodied and usage impacts are accounted for. The embodied impact is depreciated over the lifespan and usage of the related hardware components, for example as the total time spent using a device or the number of requests handled by network equipment. We describe this depreciation process per component.

The LCA methodology requires to consider multiple impact categories to build a comprehensive analysis of the environmental impacts associated with an ICT service. A description of those proposed by *Product Environmental Footprint* (PEF) recommendation [32], along with their respective units, is presented in Table II. It is important to note, as indicated in Section II, that reference environmental impact data for the rapidly evolving ICT sector remains scarce and is often restricted to a single impact category, namely climate change expressed in kg CO2e.

In the remainder of the paper environmental impacts are expressed in an abstract unit, *impact unit*. To compute the impact of a software service in a given category, *impact unit* should be replaced by the effective unit associated to the impact category under consideration.

The fuzzy set F_{em} represents the impact of the worldwide electricity mix, in impact unit per joule. However, it is possible to replace this default set with the electricity mix of a given country, or subset of countries. Furthermore, the impact of the electricity mix can vary across components to better represent the geographic dispersion of the different tiers. For instance, the end-user devices and network infrastructures may rely on the worldwide electricity mix, while the back-end infrastructures only uses the electricity mix of the country where servers are hosted.

A. Modeling End-user Device Impacts

ICT services rely extensively on ICT end devices, which can be powered either by batteries or electrical outlets. Con-

TABLE II
IMPACT CATEGORIES SUPPORTED BY OUR FRAMEWORK

PEF impact category	Impact unit	Domain
Photochemical ozone formation	kg NMVOCe	Human health
Particulate matter	disease incidence	Human health (respiratory issues)
Ionizing radiation	kBq $U^{235}e$	Human health (cancer)
Climate change	kg CO2e	Climate change
Acidification	mol H+e	Water and soil acidification
Mineral & metals resource use	kg Sbe	Abiotic resources depletion
Fossils resource use	MJ	Abiotic resources depletion
Freshwater ecotoxicity	CTUe	Ecosystems

TABLE III
INPUT VARIABLES OF THE OUTLET DEVICE MODEL, PER TYPE OF DEVICE

Variables	Unit
Embodied impact (I_e^{device})	Impact unit
Lifespan (L)	Seconds
Daily usage time (U_d)	Hours
User journey duration (T)	Seconds
Average power ($\overline{P}$)	Watts

sequently, the impact of such devices is computed through distinct hypotheses and computation formulas.

1) Outlet-powered devices: The embodied impact of outlet-powered devices is distributed over the days of their life expectancy. Consequently, the more a device is used daily, the lower its impact for each hour of usage will be. Usage impact is computed based on the power consumed by the device during the user journey, *wrt.* the location-based electricity mix.

Table III presents the variables needed to estimate the impacts of outlet-powered devices. Each variable is adapted to represent the specific type of device under study, such as desktop PCs, Consoles, TVs, or set-up boxes. Embodied impact (I_e^{device}) encompasses the impacts caused by raw material extraction, product manufacturing, transportation, and disposal or reuse. Life expectancy (L) represents the number of years of usage, and daily usage time (U_d) represents the number of hours the device is used daily, while user journey duration (T) corresponds to the time required to perform the functional unit. Power ($\overline{P}$) is the average power usage of the device. Finally, the electricity-mix impact factor (F_{em}) represents the environmental impacts associated with energy production and transport. An *impact factor* F_x gives an environmental impact per functional unit, such as `impact unit`/J for F_{em}.

All such variables are fuzzy sets to capture and propagate their associated uncertainty, and can be refined by experts based on their system knowledge. When an hypothesis is refined, its fuzzy set can ultimately be replaced with a single value. For instance, a company using the software under review on company-owned devices can use precise values for life expectancy, daily usage time, and usage time.

The impact induced by a user journey on an outlet-powered device is computed from a share of its embodied impact I_e^{device} imputed to the user journey, and the impact of the device consumption during this journey.

Then, Equation 5 models the device's embodied impact imputed to software F_e^{device}, expressed in `impact unit` per second of usage. This factor is estimated as the depreciation of the embodied impact I_e^{device} over the life expectancy of the device L, at the rate of the device's daily usage time U_d.

The software usage impact factor per second F_u^{device} is computed in Equation 6 by multiplying the electricity-mix impact factor F_{em} per second by $\overline{P}$ the average power usage of the device.

The total impact of the device I^{device} is finally estimated in Equation 7 as the sum of the embodied and usage impacts attributed to the application for the duration of the user journey T. To better represent the average user journey, the total impact is the sum of the total impacts of each type of outlet-powered device, *prorata* their respective share of the audience S. For instance, a share of the audience may watch a streamed video from a desktop, while others watch it from a TV.

$$F_e^{device} = \frac{I_e^{device} \times 24}{L \times U_d} \tag{5}$$

$$F_u^{device} = F_{em} \times \overline{P} \tag{6}$$

$$I^{device} = \sum_{d \in devices} (F_{e(d)}^{device} + F_{u(d)}^{device}) \times T \times S(d) \tag{7}$$

2) Battery-powered devices: Unlike outlet-powered devices, battery-powered devices, such as smartphones, tablets, or laptops have a lifespan closely tied to their usage. Indeed charging a battery diminishes its capacity, implying that a battery can only undergo a limited number of charge cycles before its capacity becomes unusable, mandating users to replace either the battery or the entire device. Therefore, our hypothesis assumes that the greater the software drains the battery, the higher its environmental impact is. The embodied impact of the device is thus allocated across the total energy capacity that the device can hold over its lifespan.

Table IV introduces the variables to model battery-powered devices. This hypothesis covers different types of devices, such as smartphones, tablets, and laptops, with different properties. Thus, all such variables are only applicable to a given type of device and must be duplicated according to the number of device types to consider. For instance, the average battery capacity of a smartphone $B_{cap}^{smartphone}$ is lower than the average battery capacity of a tablet B_{cap}^{tablet}. The battery embodied impact $I_e^{bat.}$ captures the various impacts of the battery (incl. manufacture, transport), and is also included in the device

TABLE IV
INPUT VARIABLES OF THE BATTERY DEVICE MODEL PER TYPE OF DEVICE

Variables	**unit**
Measured device discharge (E_d)	Amp-hour
Device embodied impact (battery included) (I_e^{device})	Impact unit
Battery embodied impact ($I_e^{bat.}$)	Impact unit
Maximum battery cycles (C_{max})	Cycles
Battery Voltage (V)	Volts
Battery capacity (B_{cap})	Amp-hour
Charger efficiency (C)	%
Battery-to-device replacement ratio (R)	%
Average batteries replacements ($\overline{R}$)	/
Share of users (S)	%

TABLE V
INPUT VARIABLES OF THE NETWORK MODEL, PER NETWORK TYPE

Variables	**Unit**
Device data transfer (D)	GB
Network type share (S)	%
Access network - Usage impact (F_u^{access})	Wh/GB
Access network - Embodied impact (F_e^{access})	Impact unit/GB
Core network – Usage impact (F_u^{core})	Wh/GB
Core network – Embodied impact (F_e^{core})	Impact unit/GB
Network average bandwidth usage (B_{net})	GB/s
CPE – Average power usage ($\overline{P}_{cpe}$)	Watts
CPE – Embodied impact (I_e^{cpe})	Impact unit
CPE - Daily usage (U_{cpe})	Seconds

embodied impact I_e. The maximum number of battery cycles C_{max} counts the maximum complete charges that the battery can sustain while remaining usable. The battery capacity B_{cap} and battery voltage V are used to quantify the drainage of the battery, *wrt.* to battery usage E_m, which is measured in a controlled environment. Meanwhile, the charger efficiency C is used to assess the actual energy usage of the device. Then, the battery-to-device replacement ratio R quantifies how frequently a user opts to replace the battery instead of the whole device when the maximum number of cycles C_{max} is reached. $\overline{R}$ is the average number of replacements that a user is willing to perform in that situation.

The primary assumption of this hypothesis is that the battery of the device has a finite number of cycles, and therefore a limited lifespan. When this lifespan is reached, the user will either replace the battery, with the probability R, or the whole device, with the probability of $1 - R$. Thus, the embodied impact of a given type of device (including its battery) $I_e^{bat.}$ is depreciated over the total quantity of energy that the battery can hold in its lifespan, $C_{max} \times B_{cap}$, as presented in Equation 8. However, when the battery is replaced (R), its embodied impact is fully depreciated over its lifespan, but only a share of the embodied impact of the remainder of the device—*i.e.*, $I_e^{device} - I_e^{bat.}$, is depreciated.

$$F_e^{bat.} = \frac{R \times (I_e^{bat.} + \frac{I_e^{device} - I_e^{bat.}}{1+\overline{R}}) + (1-R) \times I_e^{device}}{C_{max} \times B_{cap}} \tag{8}$$

For instance, if the user replaces its battery once, the device will feature 2 batteries over its lifespan, so only half of the embodied impact of the device is depreciated over the lifespan of each battery. For users replacing the whole device, the embodied impact of I_e^{device} is depreciated on this total quantity of energy. However, for users only replacing their battery, the embodied impact of the battery $I_e^{bat.}$ is depreciated over its capacity, but the embodied impact of the remainder of the device, $I_e^{device} - I_e^{bat.}$, is only depreciated over the number of batteries it will contain—*i.e.*, $\overline{R}+1$ with $\overline{R}$ being the number of replacements.

The usage impact factor $F_u^{bat.}$ of a given device type is estimated using V the voltage of the battery and the electricity-mix impact F_{em}, while accounting for C the efficiency of the charger, as reported in Equation 9.

$$F_u^{bat.} = \frac{V \times F_{em}}{C} \tag{9}$$

Both Equation 8 and Equation 9 compute an impact factor per unit of electric charge. Thus, the sum of $F_e^{bat.}$ and $F_u^{bat.}$ is the total impact factor per unit of energy, which can then be multiplied by the measured electric discharge of the user journey E_d, as modelled in Equation 10. The total impact of the functional unit on end-user devices, I^{device}, is thus the sum of the total impact of each type d of battery-powered device *prorata* $S(d)$ their respective share of the audience.

$$I^{device} = \sum_{d \in devices} E_d \times (F_{e(d)}^{bat.} + F_{u(d)}^{bat.}) \times S(d) \tag{10}$$

B. Modeling Network Layers Impacts

The network tier is composed of heterogeneous layers. The *core* network represents the internal network of the network service provider, while the *access* network is the infrastructure allowing end-users to reach this network. In addition, the *Local Area Network* (LAN) of the user can be accounted for. Notably, in fiber or xDSL networks, the user is equipped with *Customer-Premises Equipment* (CPE), but not in GSM networks. To accurately model these different technical layouts, the impact of the *core* and *access* networks, the CPE and the LAN itself, their respective impact are computed separately.

To better capture an average user journey, a combination of various types of network connections (ADSL, fiber, mobile...) is considered. In contrast to end-user devices, the network impact is not estimated *wrt.* a power usage. The geographic distribution of network components makes it challenging to precisely assess the overall consumption of a given request. Such impacts are thus estimated as an impact per unit of transmitted data.

1) Core & Access Networks: Embodied impacts are separately accounted for access F_e^{access} and core networks F_e^{core}, and usage impacts with F_u^{access} and F_u^{core}, respectively. The combined embodied impact for both core and access networks F_e^{can}, as impact unit per unit of data transmitted, is computed in Equation 11. Similarly, the total usage impact for both networks F_e^{can} is computed as the sum of energy consumption

TABLE VI
INPUT VARIABLES PER LAN EQUIPMENT

Variables	Unit
Access point bandwidth (B_{net})	GB/s
Average power usage ($\overline{P}$)	W
LAN bandwidth (B)	GB/s
Embodied impact (I_e^{lan})	Impact unit
Lifespan (L)	Seconds

per data transmitted, converted into the relevant impact factor using the electricity mix emission F_{em}, in Equation 12.

Finally in Equation 13 the resulting embodied and usage impact per data transmitted for a given network n is multiplied by the amount of data transmitted by the software D, to obtain I_{can} the total impact of the core and access network.

$$F_e^{can} = F_e^{core} + F_e^{access} \tag{11}$$

$$F_u^{can} = (F_u^{core} + F_u^{access}) \times F_{em} \tag{12}$$

$$I^{can} = (F_e^{can} + F_u^{can}) \times D \tag{13}$$

2) CPE: Wired connections—*i.e.*, fiber or xDSL—rely on Customer-Premise Equipment (CPE), such as a modem or optical network terminal. In contrast to the core and access networks, the power usage of the CPE can be empirically assessed. As such devices are outlet-powered, the impact of a CPE, denoted as I^{cpe}, can be estimated using Equation 5, Equation 6 and Equation 7, where I_e^{device}, U_d, and $\overline{P}$ are replaced by I_e^{cpe}, U_{cpe}, and $\overline{P}_{cpe}$, respectively.

3) LAN: Finally, the LAN of the user is modeled as a set of equipment including firewalls, switches, and WiFi access points. As for the CPE, the LAN impacts are quantified *wrt.* a usage time. The associated variables are listed in Table VI.

The embodied impact of the devices is depreciated over their average lifespan, *prorata* their usage ratio in Equation 14, by providing a depreciation in impact factor per unit of time. Similarly, the sum of energy consumptions of all the LAN components is converted into impact factor per unit of time F_u^{lan} by reusing Equation 6. The resulting embodied and usage impacts per unit of time are then summed and multiplied by the usage duration—*i.e.*, the transmitted data D divided by the network speed—in Equation 15.

$$F_e^{lan} = \frac{I_e^{lan} \times B_{net}}{L \times B} \tag{14}$$

$$I^{lan} = \frac{D}{B_{net}} \times \sum_{q \in eq} (F_{e(q)}^{lan} + F_{u(q)}^{lan}) \tag{15}$$

4) Total: The total impact of the network I_n is then computed in Equation 16 as the sum of impacts of the core and access networks, the CPE, and the LAN for all network types, *prorata* $S(n)$ the share of users behind such network. For network without CPE, I_n^{cpe} is 0, while software only used within a company may have a network mix of 100% fiber, with CPE and LAN. Contrarily, software used by users on their own device use a network mix, such as 50% 5G, no CPE and no LAN, and 50% fiber, with CPE and no LAN.

TABLE VII
INPUT VARIABLES OF THE BACK-END MODEL

Variables	Unit
Request count (N_r)	/
Server max requests per second (N_{rps})	/
Server embodied impact (I_e^{server})	Impact unit
Server lifespan (L)	Seconds
Server average usage (load) (U)	/ (%)
Average power usage ($\overline{P}$)	Watts
Power usage efficiency (PUE)	/

$$I^{network} = \sum_{n \in network} (I_n^{can} + I_n^{cpe} + I_n^{lan}) \times S(n) \tag{16}$$

C. Modeling Back-end Infrastructures Impacts

The back-end tier estimates the environmental impact of servers *wrt.* to the requests executed by the software during a given user journey.

I_e^{server} represents the embodied impact of a server, which is deprecated over the maximum number of requests that this server will handle throughout its lifetime $L \times N_{rps} \times U$, to obtain an embodied impact unit per request handled, $F_e^{backend}$.

To assess the usage impact of servers, the usage impact factor per request $F_u^{backend}$ is computed in Equation 18. It is the total impact per second $\overline{P} \times PUE \times F_{em}$ of the server, divided by the average number of requests handled every second $N_{rps} \times U$.

Finally, to estimate the server's total impact, the embodied and usage impacts per request are multiplied by the number of requests performed during the user journey N_r in Equation 19.

$$F_e^{backend} = \frac{I_e^{server}}{L \times N_{rps} \times U} \tag{17}$$

$$F_u^{backend} = \frac{\overline{P} \times PUE \times F_{em}}{N_{rps} \times U} \tag{18}$$

$$I^{backend} = (F_e^{backend} + F_u^{backend}) \times N_r \tag{19}$$

D. Combining Impact Models

Finally, the total impact of a single execution of the user journey under review, I_t, is computed in Equation 20 as the sum of the devices, network, and back-end impacts induced by the user journey—*i.e.*, the functional unit.

$$I = I^{device} + I^{network} + I^{backend} \tag{20}$$

To be compliant with ICT services functional unit [3], [6], this value representing a single reference scenario should be multiplied by the total number of executions by all users over a period of time.

V. MODEL APPLICATION

This section reports on a practical application of the models introduced in Section IV, aiming to illustrate the results derived and the impact of fuzzy logic on the outcomes. Then, the section explores some potential strategies to reduce the observed uncertainty.

TABLE VIII
SELECTED HYPOTHESES TO APPLY THE APPROACH

Variables	**Unit**	**Fuzzy set** L	m_L	m_R	R	**Central value**	**Uncertainty (%)**
Input							
Measured discharge (E_m)	Ah	0.0267	0.0267	0.0267	0.0267	0.0267	0
Device data transfer (D)	GB	0.0031	0.0031	0.0031	0.0031	0.0031	0
Measured request count (N_{rq})	/	200	200	200	200	200	0
Electricity-mix impact (I_{em})	gCO2e/J	0.0001	0.0002	0.0003	0,0005	0.0002	±24.11
Hypotheses - End-user device							
Device & battery emb. impact (I_e^{device})	KgCO2e	31.41	48.75	65.62	101.84	57.18	±14.74
Battery emb. impact ($I_e^{battery}$)	KgCO2e	0.72	1.17	1.63	2.62	1.40	±16.47
Maximum battery cycles (C_{max})	Cycles	328.72	500.07	661.16	1,005.79	580.61	±13.87
Battery Voltage (V)	V	3.79	3.81	3.82	3.84	3.81	±0.12
Battery capacity (B_{cap})	Ah	1.73	2.62	3.45	5.23	3.03	±13.71
Charger efficiency (C)	/ (%)	0.59	0.68	0.75	0.87	0.72	±4.13
Battery/device rep. ratio (R)	/ (%)	0.09	0.17	0.29	0.55	0.23	±25.41
Average batteries replacements ($\overline{R}$)	/	0.81	1.29	1.77	2.82	1.53	±15.79
Share of users (S)	/	1	1	1	1	1	0
Hypotheses - Network							
Access Network usage (F_u^{access})	Wh/GB	34.98	94.93	290.65	788.84	192.79	±50.76
Access Network emb. (F_e^{access})	kgCO2e/GB	0.012	0.018	0.030	0.035	0.023	±25.00
Core Network usage (F_u^{core})	Wh/GB	2.69	7.53	24.91	69.75	16.22	±53.56
Core Network emb. (F_e^{core})	kgCO2e/GB	0.0004	0.0009	0.0021	0.0050	0.0010	±39.09
Hypotheses - Back-end							
Core requests per second (max) (N_{rps})	/	292	320	499	518	409	±21.85
Server emb. impact (I_e^{server})	KgCO2e	427.06	1,018.65	2,383.90	5,686.25	1,701.28	±40.12
Server lifespan (L)	Years	9.2E7	1.2E8	1.3E8	1.7E8	1.2E8	±6.85
Server average usage (load) (U)	/ (%)	1	1	1	1	1	0
Average power ($\overline{P}$)	Watts	165.49	282.68	417.38	712.94	350.03	±19.24
Power usage efficiency (PUE)	/	1.30	1.62	1.84	2.30	1.73	±6.41

A. Application of the Approach

To illustrate our approach, we introduce an example application scenario. This user journey is exclusively performed on smartphones, using a 5G connection and, therefore, not relying on CPE or LAN equipment. For a specified user journey of this mobile app, 26.7 mAh was consumed by the device and 3.1 MB of data was conveyed by 200 network requests. This user journey is considered worldwide and relies on the global electricity-mix impact factor. The assessment focuses solely on the CO2e emissions associated with this user journey.

Table VIII introduces the values used for this specific scenario, including the measured data used as inputs, as well as the hypothesis regarding the values of each variable. These values are provided for illustrative purposes and should not be considered as the state of the art, as they should be tailored for each software service context. To illustrate their respective weight on the total uncertainty, this table also contains the central value and uncertainty of each hypothesis. This uncertainty is estimated with the core method [33], using the average between m_L and m_R as the central value, and the difference between this central value and m_L and m_R as the symmetric margin of uncertainty. The results are presented as the *before* scope in Figure 2, while the *after* one corresponds to an uncertainty reduction is discussed later.

The estimated impact of the end-user device is composed of 0.8 gCO2e of embodied impact and 0.1 gCO2e of usage impact. In this specific use case, the imputed embodied impact is an order of magnitude larger than the usage impact. Thus, the impact of this application is caused by the reduction of the lifespan of the device, rather than by the production of energy.

This trend is reverted for network and back-end infrastructures. Indeed, such infrastructures are largely mutualised, hence enforcing a dilution of their respective embodied impacts. Therefore, their imputed embodied impact can be limited compared to their usage, depending on the electricity mix. Specifically in our use case, the impact of the network is composed of 0.1 gCO2e of imputed embodied impact and 0.5 gCO2e of usage impact. The impact of the server is composed of less than 0.01 gCO2e of imputed embodied impact and 0.7 gCO2e of usage impact.

The total impact for a user journey is the sum of the impacts of the average end-user's device, network, and back-end. In particular, the device, network, and back-end represent 57%, 38%, and 5% of the total impact, respectively. This impact is composed of 55% of imputed embodied impact. Thus, our recommendation to reduce the impacts of such a mobile application would be to focus on optimizing its power usage, affecting the lifespan of the device, rather than its data usage, affecting network and back-end layers.

The impact assessment results are strongly correlated to the measured power and data usage, as well as the electricity mix. For instance, reducing the power usage and increasing the data usage of the mobile application would shift the impacts toward network and back-end layers. Similarly, altering the electricity mix would mostly affect the allocation between imputed embodied impacts and usage impacts.

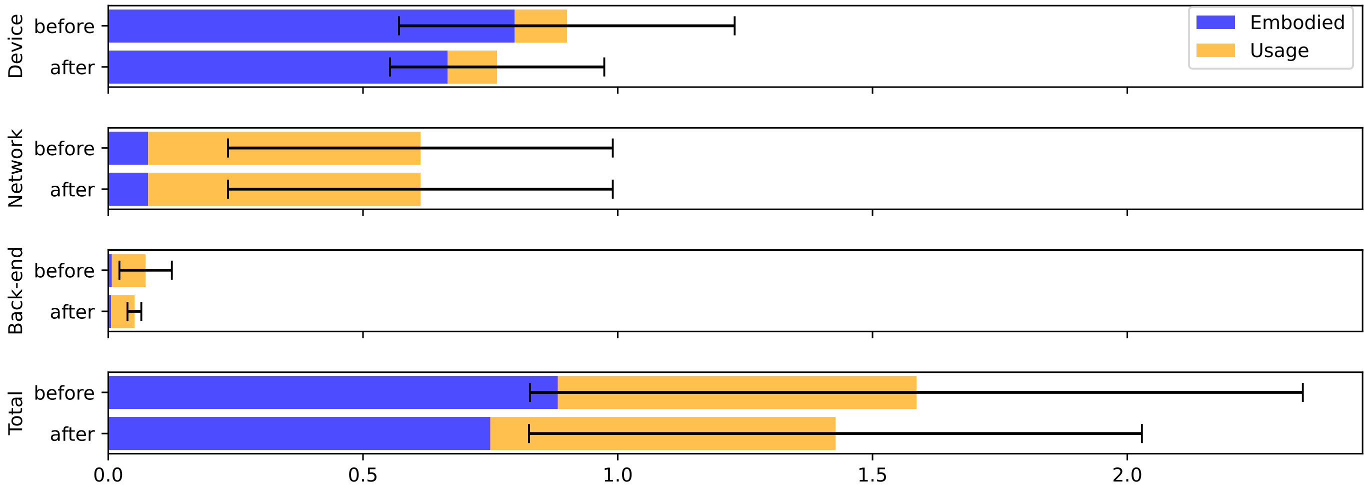

Fig. 2. Estimated impacts of an example user journey, before and after uncertainty reduction (gCO2e).

B. Reducing Uncertainty

Fuzzy logic allows for propagating uncertainty at all calculation steps. Due to the high uncertainty caused by divergences in sources and the high number of modeling hypotheses, the uncertainty of the result is also high. However, such hypotheses can be refined to better capture the user journey under review. For instance, the estimated power usage of servers, computed based on a collection of sources regarding a set of servers, is represented as a fuzzy set. Such a fuzzy set can be replaced by a fixed value, obtained through physical measures or additional information regarding the specific servers used by the application. The process of specifying variables allows experts to significantly reduce the uncertainty of the result.

Some hypotheses are better candidates for reducing uncertainty. For instance, the charger efficiency or battery capacity of the battery component cannot be fixed for publicly available software, as such hypotheses must remain representative of the population of users. However, when the regarded application is used on a fleet of company-maintained devices, such hypotheses can be fixed to the specific deployed hardware. Contrarily, the uncertainty of network impacts is particularly challenging to reduce. Such infrastructures are inherently largely mutualised and geographically scattered, affecting the ability to provide exact values.

In the example user journey introduced above, only the minimal amount of parameters are specified—*i.e.*, the measured discharge, the amount of transferred data, and the request count. To illustrate the effect of specifying additional variables, hypotheses can be modified with more precise information regarding the software characteristics. To demonstrate the impact of such a process, the above-introduced use case can be specified with the following data. End-user devices are owned and provided to users by the company using the application. A single model of device is issued, with a 4Ah and 3.8V battery, delivered with a charger with an efficiency of 75%. The company does not plan to replace the battery when failure occurs. The application relies on a 400W server that can handle 500 requests per second, in a data center with a PUE of 1.4. These values replace the respective hypothesis and thus reduce their respective uncertainty to 0. The results of these hypotheses replacement by real values are available in the *after* scope of Figure 2. The other hypotheses of this application are the default variables introduced in Table VIII. While to final result is not dramatically different, the uncertainty is substantially reduced.

In particular, the uncertainty of the device impact is reduced from ±36%, to ±27%. The uncertainty of the back-end layer is reduced from ±62%, to ±26%. As a consequence, the uncertainty of the total impact is reduced from ±47%, to ±42%. The remaining overall uncertainty is largely caused by the uncertainty of the network layer, which can not be reduced for the reasons introduced above.

> **RQ2:** Following LCA methodology, data is collected and normalized according to a functional unit. The accomplishment of this functional unit affects not only the end-user device, but also the underlying networks and back-ends, which are thus accounted for in the impact assessment. However, data is not always accessible for all three tiers of the software services architecture, implying modeling hypotheses associated with a high level of uncertainty. Particularly, the embodied impact of ICT devices should be depreciated according to their usage, which spans further uncertainties. For each of these modeling hypotheses, the adoption of fuzzy logic enables systematic tracking and propagation of uncertainties throughout computation steps.

VI. Discussion

From a scientific perspective, the LCA method lacks empirical validation regarding the overall result [34]. Therefore, even if using fuzzy logic in ICT services LCA offers a systematic approach to evaluate and propagate uncertainties, the outcome keeps lacking empirical validation. A comparison with the standard Monte Carlo method would not be relevant, as fuzzy logic not only enables the propagation of uncertainty, but also provides an aggregation method for secondary data sources.

Furthermore, it is also significantly influenced by the secondary-origin data used to build a set of hypotheses regarding the environmental impact of considered functional units. Ultimately, the quality of estimations is largely constrained by the quality of such sources and the hypothesis derived from them. In particular, environmental impact data sources are still scarce (cf. Section II), and certain impact categories are almost not quantified at all. For instance, to the best of our knowledge, very few sources address the environmental impacts of network infrastructures in other categories than climate change.

a) End-user devices: It is assumed that the lifespan of battery-powered devices is solely determined by the lifespan of their battery and that users replace their devices when the battery becomes unusable. However, such a hypothesis may overlook other factors influencing the decision to replace these devices. Specifically, hardware and software obsolescence are not accounted for. Battery-powered devices, such as older smartphones, can be replaced due to slowness when executing recent applications, outdated operating systems unsupported by newer applications, or the availability of newer models in the market.

Similarly, it is assumed that the lifespan of outlet-powered devices is fixed and independent of their usage. As the embodied impact of these devices is depreciated over their daily usage, increasing usage reduces the impact per unit of time. However, higher usage may also lead users to replace their devices earlier, thus increasing this impact factor. Such considerations are not modeled as they are particularly difficult to detect and quantify. Due to these different hypotheses, the modeling of battery-powered and outlet-powered devices diverges. In low-impact electricity mixes, increasing the usage of battery-powered devices increases their total impact, whereas increasing the usage of outlet-powered devices diminishes their total impact. Such divergences require specific explanations when discussing the analysis outcomes.

b) Network: The network component relies on hypotheses regarding the imputed embodied impact and usage impact of such infrastructures. Such hypotheses are expressed as energy or impact units per amount of data transmitted and are drawn from the literature with no additional imputation formula. Indeed, the network is considered as a black box. The exact network topology of an average user is not reasonably ascertainable, and thus such hypothesis can not be specified. Thus, the uncertainty of network impacts can not be reduced. The total uncertainty of the results remain high after specifying hypotheses regarding end-user devices and back-end infrastructures. Therefore, additional research on the specific impact of the network is necessary in future work, to improve this component and reduce uncertainty when specific information are available regarding the network.

c) Back-end: Finally, the modelling of back-end infrastructures faces some limitations. The embodied impact of a server is allocated to the maximum number of requests it can handle throughout its lifespan. This hypothesis assumes that the hardware operates at maximal load during its entire lifespan, which is largely an overestimation [35]. Consequently, the result of the back-end layer may be underestimated. If the server only receives half of the maximum requests per second, then the impact factor of each request would be twice as high.

Furthermore, the inventory data is collected according to LCA methodology, *wrt.* to the functional unit. This means that a *black-box* approach is used for back-ends, assuming a set of requests rather than the technical processes involved in handling such requests. This can lead to significant underestimations, as the infrastructure considered only includes the server, excluding components such as management layers, virtualization, or storage. Finally, third-party services that can be integrated to the software are not accounted for, such as analytics or external content. All requests toward such services are imputed to the back-end of the software under review.

In future work, finer modeling of back-end infrastructures and data centers may offer more representative estimations.

VII. Conclusion

Due to the intricate complexity, rapid evolution, and geographical distribution of ICT services, conducting life cycle assessments to evaluate their potential environmental impact is a challenging endeavor. It requires the adoption of modeling hypotheses, which inherently entails high uncertainties in the estimation outcomes. Furthermore, these assessments heavily rely on secondary data, which are still scarcely available and with varying quality. However, these uncertainties are not often adequately quantified in ICT-related LCAs.

In this paper, we introduce an approach based on fuzzy logic to track both the uncertainty arising from secondary data, and modeling choices. We propose hypotheses compliant with ICT services LCA principles to assess the embodied and usage impact across the end-user device, infrastructure, and back-end for a given functional unit. To deal with these uncertainties, we leverage fuzzy logic to aggregate multiple sources, weighted by their respective *Data Quality Index* (DQI), to obtain more representative estimates of the state-of-the-art. We demonstrate how fuzzy logic improves the quality of results by systematically propagating uncertainties to identify their primary sources, aiming to mitigate them.

In future work, we intend to improve hypotheses by tackling their current limitations, in particular regarding the back-end impacts of larger projects involving, for instance, *Content Delivery Networks* (CDN).

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