Evaluating the (ir)relevance of IoT solutions with respect to environmental limits based on LCA and backcasting studies

The case study of smart public lighting in Wallonia, Belgium (2020-2050)

Thibault Pirson
thibault.pirson@uclouvain.be
Université catholique de Louvain
Louvain-la-Neuve, Belgium

Louis Golard
louis.golard@uclouvain.be
Université catholique de Louvain
Louvain-la-Neuve, Belgium

David Bol
david.bol@uclouvain.be
Université catholique de Louvain
Louvain-la-Neuve, Belgium

ABSTRACT

Significant efforts in academia and industry are devoted to studying and improving the resource and energy efficiency enabled by the Internet of Things (IoT). At the same time, the global pressure of humanity on the environment keeps on increasing, calling for radical changes in the organization of our developed societies. In this context, the increasing use of IoT to support smart applications in fields such as city and building management, farming, and healthcare, raises sustainability concerns as it is calling for a massive deployment of smart IoT edge devices. In this paper, we hence investigate what strategy should be used to help keeping IoT deployment within environmental limits, while taking advantage of its benefits where it is relevant. We first build on existing literature to show that improving the environmental performance of a product through conventional life-cycle assessment (LCA) and ecodesign is not sufficient to guarantee environmental sustainability. As this is a recurrent shortcoming in conventional LCA of ICT, we argue that LCA should be integrated in a broader framework, to ease the inclusion of both direct and indirect environmental effects. By exploring future-oriented studies, we show that using a *backcasting* approach consistent with Paris Agreement goals has far more potential than the conventional forecasting approach used in ICT studies so far. We illustrate this on the case study of smart public lighting in Wallonia, Belgium for the period 2020-2050, and evaluate the direct impacts of this real-life IoT solution through a full-scope multi-indicator LCA.

KEYWORDS

Sustainability, life cycle assessment (LCA), backcasting, Internet of Things (IoT), smart public lighting, planetary boundaries, rebound effects, ecological research.

ACM Reference Format:
Thibault Pirson, Louis Golard, and David Bol. 2023. Evaluating the (ir)relevance of IoT solutions with respect to environmental limits based on LCA and backcasting studies: The case study of smart public lighting in Wallonia, Belgium (2020-2050). In *LIMITS '23: Workshop on Computing within Limits, June 14-15, 2023.* 14 pages. https://doi.org/xxx

LIMITS '23, June 14–15, 2023, Online

https://doi.org/xxx

1 INTRODUCTION

Over the last decades, the rapid development of information and communication technologies (ICT) has deeply shaped our modern societies. More specifically, a sub-part of ICT called the Internet of Things (IoT) has gained significant momentum both in academia and industry. The IoT connects physical *things* to the Internet by embedding electronics in everyday objects, hence supporting ubiquitous computing. This has led to a steep growth of IoT devices over the last years, with estimates projecting up to 200 billion connected objects in 2030 [53]. In developed countries, the IoT plays a key role in digitalization and is generally seen as an important building block to realize projects such as circular economy, or smart cities and buildings, agriculture, mobility and healthcare [36].

Given the environmental context and the urgent need to reduce greenhouse gas (GHG) emissions at the world scale, several studies have focused on quantifying the environmental benefits and burdens of ICT over the last years [19, 23, 32, 44]. For instance, the carbon footprint of the ICT was evaluated at about 1.2-2.2 $GtCO_2eq$ in 2020, which corresponds to about 2.1-3.9% of worldwide GHG emissions [23]. Yet, ICT are also often presented as an effective solution for decreasing the environmental footprint of other sectors, mostly thanks to optimization and substitution effects [7, 19, 34]. Some reports hence claim that ICT's environmental benefits can be several times greater than their own environmental burden [19]. Nevertheless, the quantification of these benefits generates a lot of controversy, as the global pressure of humanity on the environment keeps on increasing [38, 64]. This suggests that benefits attributed to ICT may be overestimated [7, 56]. Rasoldier et al. [56] specifically addressed this point and raises the question "How realistic are claims about the benefits of using digital technologies for GHG emissions mitigation?". By pointing out critical issues related to environmental sustainability in ICT, their study clarifies recurrent issues and propose a set of guidelines that all studies working on the mitigation of GHG emissions through digital solutions should satisfy. In particular, they stress out that (1) direct environmental impacts have to be evaluated in all cases, which is commonly done through LCA, and that (2) global strategies aligned with sustainable pathways should be considered, although it is almost never the case.

Even if these two observations target the ICT as a whole, this also applies in the specific case of IoT. Indeed, previous studies [14, 23, 53] point out a critical lack of LCA for IoT devices, leaving their environmental impacts vastly under-explored. Then, although we showed in a previous study [53] the existence of clear conflicting trends between the carbon footprint evolution of the massive IoT production and the GHG trajectory needed to reach the 1.5°C target set by the Paris Agreement, we did not considered indirect effects [7] nor proposed a strategy to keep IoT deployment within environmental limits. Consequently, the question "*how* to achieve this in practice?" remains open, and echoes the essential need to plan for actionable future(s) of "limits and/or scarcity" that are "fundamentally different from the extrapolation of current trends" [21, 50].

1.1 Contributions

In this paper, we therefore investigate what strategy could be used to help keeping IoT deployment within environmental limits. We first build on existing literature to show that improving the environmental performance of a product through LCA and ecodesign is not sufficient to guarantee environmental sustainability. Then, we illustrate this general limitation in the specific case of using IoT for smart public lighting. We start by carrying out a full-scope multi-indicator LCA of a real-life IoT solution for smart public lighting. This LCA is *per se* valuable as it brings knowledge about the environmental impacts of an IoT solution, but it falls short of assessing the contribution towards sustainable public lighting because we only accounted for the direct impacts. As this is a recurrent shortcoming in conventional LCAs of ICT [7], we propose to integrate LCA in a broader framework to consider the indirect effects. Consequently, we explore future-oriented studies and show that *backcasting* is a well-suited approach to discriminate between IoT solutions that should be deployed and the ones that should be discouraged for ecological reasons. We illustrate this on the case study of smart public lighting in Wallonia, Belgium over the period 2020-2050. By considering Paris Agreement targets, we build upon the "Carbon Law" approach [50, 60] and proposes a concrete step towards limits-aware research in ICT [7, 16, 21].

1.2 Outline

The rest of this paper is structured as follows. In Section 2, we briefly remind background concepts regarding mainly the terminology of direct and indirect effects of ICT applied to the field of IoT. Then, Section 3 highlights the limits of LCA as a tool for environmental sustainability. In Section 4, we carry out an in-depth full-scope LCA for a real-life IoT smart solution deployed in Wallonia, Belgium. Finally, Section 5 provides a streamlined backcast with IoT scenarios to illustrate the usefulness of backcasting. Conclusions and future works are outlined in Section 6.

2 GENERAL BACKGROUND AND TERMINOLOGY

The environmental sustainability framework introduced by Berkhout and Hertin [4] and popularized by Hilty et al. [33] offers a simplified view of ICT as being at the same time "part of the solution" and "part of the problem". Albeit this classification is conceptually appealing as it tends to classify what fosters environmental sustainability and what does not, it embeds inherent shortcomings especially by considering that the different effects are independent. The authors themselves questioned the normative aspect of that conceptual framework (positive and negative contributions) because it creates misunderstandings and misleading messages depending on the perspective that is considered [33], which is further supported in [28]. Hilty and Aebischer even stress out that "the idea of ICT being either good or bad for the environment should be combated" [33], and they proposed an updated version of the framework, named "LES model" [33]. Although imperfect, these frameworks have something in common: they are useful to structure different levels of abstraction in order to address questions related to ICT and environmental sustainability. As originally introduced by Berkhout and Hertin [4], three types of environmental effects are clearly distinguished:

- *Direct* effects capture the environmental burdens generated by the production, use, and disposal of ICT equipment. This includes all the environmental effects associated with the life cycle of ICT products, ranging from raw material extraction, resource use, emissions, and management of e-wastes. These effects are focused on the technological level.
- *Indirect* effects refer to all actions that are enabled by the use of ICT, hence focusing on the application level.
- *Structural and behavioral* effects relate to the more fundamental changes in socio-economic system, including impacts on life styles, value systems, and the dynamics of the economic system. They occur at a macroscopic level.

Similarly to ICT, the IoT may enable optimization and substitution effects at the application level, e,g., IoT could enable remote control and predictive maintenance, or efficiency improvements in essential systems including food, water, transportation and energy. IoT could also foster a more circular economy by supporting product traceability and transparency across value chains: e.g., through digital twins and digital product passports. Yet, at the same time, the IoT generates undeniable environmental burdens. For instance, the carbon footprint of global IoT production is estimated to be between 22 and 1120 $MtCO_2eq$ in 2027 [53], depending on the deployment scenario. Unfortunately, although few studies consider the direct environmental effects of IoT, mainly through LCA [11, 12, 36, 37, 42, 43, 53, 55, 69], they are usually completely overlooked [23, 53]. The deployment of an IoT solution may also lead to induction and obsolescence effects, e.g., by inducing transportation to maintain the IoT infrastructure and by making older systems obsolete if they are not compatible or less appealing. One could also think about a *buzzword* effect which may drive new products to include emerging technologies in order to be branded as *high-tech* [10]. IoT can also be fertile ground for rebound effects [25, 53] that are likely to be significant in digital technologies, as pointed out by the IPCC [38]. Finally, the expanding dependence on digital tools and services can be seen as an emerging risk.

Once the direct environmental impacts of a given ICT solution have been assessed through LCA or improved through ecodesign, the natural next step is to compare that burden with the expected benefits enabled by the solution [51] to estimate the *net environmental balance* [36]. Although it is tempting, we argue that we should avoid evaluating the environmental net balance by comparing the different contributions of "ICT as a solution" and "ICT as a problem" in Hilty's framework. In fact, this environmental balance would generally focus on the first-order environmental benefits, for instance the reduction of electricity consumption or the avoided on-site interventions of technicians thanks to predictive maintenance. This would elude higher-order effects such as induction, rebound effects, and obsolescence [7, 25, 41, 58], which are more difficult to evaluate but clearly exist. Consequently, assessing the direct impacts of IoT is an important step, but there is a need to go beyond the estimation of the net environmental balance and to propose comprehensive studies to guide the IoT deployment within environmental limits. Sections 3 and 4 focus on direct impacts whereas Section 5 integrates indirect effects in a broader framework that addresses global environmental limits.

3 GENERAL LIMITS OF LCA AS A TOOL FOR ENVIRONMENTAL SUSTAINABILITY

LCA is a structured, comprehensive and internationally standardized methodology to quantitatively evaluate the *potential* environmental impacts of a product (a good or a service) throughout its whole life cycle including raw-material extraction, production, use, and end of life [29, 39]. This methodology support the quantification of all relevant emissions and resources consumed by the product, together with the associated environmental and health impacts or resource depletion issues. LCA is generally used for different goals, including for instance environmental communication, decision making, and product improvement (i.e., *ecodesign*) [29]. It is widely recognized as a very useful methodology to (i) show "how a specific functionality can be achieved in the most environmentally friendly way among a predefined list of alternatives", or (ii) to "show in which parts of the life cycle it is particularly important to improve a product to reduce its environmental impacts" [29].

Nevertheless, as explained in [8, 29], if LCA helps to do *better* by reducing the direct environmental impacts of a given product, it cannot help to evaluate whether the environmental performance are *good enough* in the context of global environmental limits. In fact, such a product-oriented analysis hardly relates to *absolute environmental sustainability* where global limits such as planetary boundaries are not exceeded [8, 64]. An interesting attempt to link LCA results to planetary boundaries is proposed in [9] where the authors developed *carrying capacity* references for the normalization step of LCA, aiming to translate the LCA results into corresponding occupied *carrying capacities* (in person equivalents). The concept of *carrying capacity* is defined by [9] as "the maximum sustained environmental intervention a natural system can withstand without experiencing negative changes in structure or functioning that are difficult or impossible to revert". This could therefore be understood as the boundary between global environmental sustainability and unsustainability [9]. Yet, this approach does not modify the functional unit of the LCA as it only changes the reference situation of the normalization step. In the rest of this section, we further investigate this inherent limitation of LCA to highlight that although it is a very useful tool to assess the environmental impacts of a product and to support its ecodesign, LCA is not sufficient to ensure absolute environmental sustainability [8].

The *eco-efficiency* could be defined as the environmental performance of a product, as defined by its functional unit. Using LCA

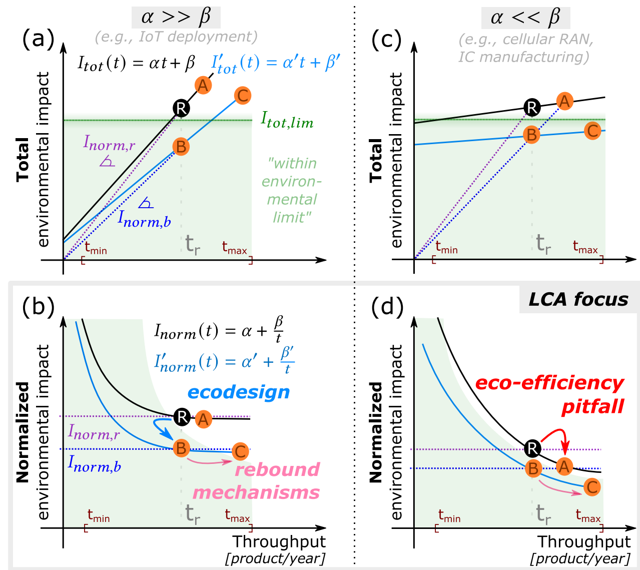

Figure 1: Illustration of the eco-efficiency pitfall by considering the coexistence of (a) the total environmental impacts of a given production, and (b) the corresponding environmental impact normalized per product. Figure inspired by [30].

to support eco-efficiency optimization falls in the same paradigm as optimization of other conventional key performance indicators (KPIs), even if the eco-efficiency targets environmental metrics rather than economic or technical metrics [54]. A very simple yet realistic model, inspired by [8, 30], is proposed in Figure 1 to support the conceptual explanation of the eco-efficiency pitfall by connecting the absolute and relative environmental impacts. Figure 1(a) formulates the total annual environmental impacts $I_{tot}(t)$ as a linear function of the product throughput t, i.e., the functional products fabricated (or deployed) per year: $I_{tot}(t) = \alpha t + \beta$ where α is the throughput sensitivity, i.e., the marginal environmental impact per product, and β the fixed environmental impacts. For a given reference throughput t_r, the environmental impact per product can be obtained by dividing the total annual environmental impacts by the product throughput. This corresponds to the eco-intensity (the inverse of the eco-efficiency) $I_{norm}(t_r) = \alpha + \frac{\beta}{t_r}$, which is the slope of the line between the reference situation R and the origin, as shown in Figure 1. Practical examples illustrating this simple model can be found in [3, 15, 24, 54, 68]. The throughput is likely to be upper-bounded by a maximum practical production (or deployment) capacity t_{max} and lower-bounded by a minimum sale level t_{min} that brings economic profitability. In the context of planetary boundaries, an "environmental ceiling" [57] could also be defined to set an upper bound on the total environmental impacts, as illustrated in Figure 1(a) by $I_{tot,lim}$. Nevertheless, the definition of this ceiling at the scale of a specific product implies complex arbitration and allocation between socio-economic actors and sectors, which is far from obvious but hopefully not impossible [8]. This echoes the idea of carrying capacity references mentioned above.

Building upon the recent work initiated in [30], we use our conceptual model to point out the effect of alternative situations on both the absolute and relative environmental impacts, as shown in Figure 1. This illustrates that a better eco-intensity can be reached in situations A, B, and C although they are very different in nature. We define the *eco-efficiency pitfall* as the situation A in which the eco-intensity is improved through the increase in throughput, but results in higher total environmental impacts. For a very large throughput (mass production), the eco-intensity tends towards a minimum limit equal to α. Intuitively, this corresponds to the situation in which the fixed environmental impacts are amortized over a large number of products. On the contrary, the improved eco-efficiency is reached for a throughput very similar to t_r in situation B thanks to ecodesign, hence providing a reduction of the total environmental impacts as illustrated by $I'_{tot}(t_r) = \alpha' t_r + \beta'$. Finally, if the throughput is kept the same while conducting ecodesign, absolute environmental impact savings can be expected. Nevertheless, even an eco-designed product can be subject to rebound mechanisms [25, 31, 41], which could reduce (or cancel out) the expected savings. This is captured by situation C in Figures 1(a)-(b).

It is crucial for LCA practitioners and for people using the results of LCA to be aware that striving for an ever more eco-efficient product offers no guarantee to improve the global environmental situation. Given the current environmental context, it is critical to ensure that LCA is not used to legitimize a situation where incremental insufficient eco-efficiency improvements are targeted and reached [8]. This is especially important in the field of IoT mostly because of the wide diversity of applications that are targeted, together with the diversity of solutions coexisting for each application [5, 53]. The next section aims at illustrating this in practice by conducting the LCA of an IoT solution.

4 USING LCA TO ASSESS THE DIRECT IMPACTS OF A REAL-LIFE DISTRIBUTED IOT NETWORK FOR SMART LIGHTING

In this section, we carry out an in-depth full-scope LCA to evaluate the direct impacts of a real-life IoT network on a specific case study of IoT smart public lighting. This solution implements the remote control of public lights (mainly remote dimming) and enables predictive maintenance for each streetlight. The IoT solution gathers two types of nodes in the IoT area network: (1) an IoT node per light fixture, and (2) a gateway intended to connect several nodes to the cloud through a mobile 4G connection. One gateway usually serves about one hundred IoT nodes, which are connected in a mesh topology using the Wirepass protocol (2.4 GHz) [71]. The IoT solution does *not* implement edge sensing for the real-time detection of pedestrians or cars.

4.1 Methodology

We use a bottom-up attributional LCA approach, based on real-life scenarios according to one public road in Belgium. Although primary data is hard to access for ICT devices and electronic components [53], the major part of the data used in this study were provided by a company[1] currently developing and deploying smart lighting solutions at large scale. In addition, the company answered a detailed survey designed by the authors to obtain the specific details needed to derive realistic modeling assumptions. In order to evaluate the variability of our modeling, we define a set of *low*, *typical* and *high* values for each parameter.

4.2 Modeling assumptions

This section provides the main modeling assumptions underlying the LCA carried out in this study. Simplified bill of materials for both the IoT node and the gateway are provided in the Appendix, together with the a schematic map of the deployment site.

- **Goal.** The goal of this LCA is to assess the environmental impacts of a real-life deployed IoT solution for smart public lighting. The results are then intended to be used in the context of future-oriented scenario modeling.
- **Functional unit.** The functional unit is a real-life IoT network with N_{nodes} = 108 IoT nodes and $N_{gateway}$ = 1 gateway, working 24/7 during 10 years, and controlling the public lighting over approximately 3 km of public road.
- **System boundaries.** This study considers a cradle-to-grave system including life-cycle phases and processes from raw-material extraction, production, transport, deployment, use, maintenance, decommissioning, and end of life, as illustrated in Figure 2. The use of existing ICT infrastructure for data transfer is also taken into account, but the impacts associated with the production of this infrastructure are not included.
- **Impact categories.** This study covers several impact categories, mainly from the ReCiPe 2016 v1.1 (H) midpoint and the CML 2001 methods, as shown in Table 2.
- **Software and databases.** We use the Sphera LCA software[2] with the professional and extension XI (electronics) databases [63], for their high level of details on electronic components, their extensive documentation, and state-of-the-art data about electronics and semiconductors [53, 54].

The Sphera LCA databases were used to model the **raw-material extraction** and the **production** of the different electronic components such as integrated circuits (ICs), printed circuit boards (PCBs), passive components, casings, etc. As the majority of modules were not directly available in the database, custom models have been developed in Sphera LCA. This was the case for the 4G LTE connectivity module, the Bluetooth module, the WiFi dongle, the antennas, the Raspberry Pi 2, several system in packages chips involved in processing and memory tasks, and the GPS module. All materials used in our models are virgin materials, no recycled material.

Regarding the **transport**, all models are based on the joint consideration of distance and mass to be transported (in kg·km), where the mass considered is the sum of the product's mass and its packaging. The components are transported from China to the assembly site by container, and the intermediate steps between the dispatching site and the clients are modeled assuming a transport by truck, or plane for the worst-case modeling.

[1] The company wants to remain anonymous.
[2] Sphera LCA was previously called GaBi

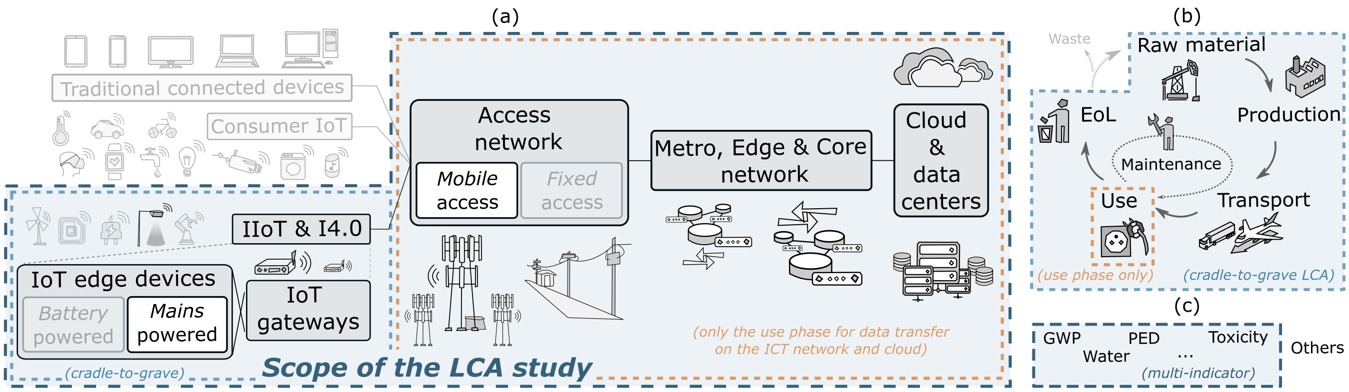

Figure 2: Scope of the LCA carried out in this study. (a) Schematic IoT network representation. (b) Life cycle phases. (c) Impact categories. The complete list of indicators is provided in Table 2.

For the **use phase**, we consider both the nominal specifications from datasheets and the information from the company based on electrical characterization during operation. The power consumption for the gateway is ranging from 3 to 5 W (typical 4 W) whereas the IoT nodes consume between 0.3 to 1.92 W (typical 0.6 W). Both the nodes and the gateway are powered by the electric grid, as they are connected to the light fixture's main power supply through the Digital Addressable Lighting Interface (DALI) connection. The power consumption overhead due to the communication in the Wirepass mesh network is already included in the use phase power consumption. To model the data transfer from the gateway to the cloud **using the existing ICT infrastructure**, we applied electricity intensity factor in kWh/GB for the radio access network (RAN), the metro-core network (MC), and the datacenters (DC) and cloud. These factors have been defined through a systematic review of the literature which goes beyond the scope of this study, but the energy intensity factors considered for the LCA are provided in Table 1. The EU28 electricity grid mix is used for the use phase.

Table 1: Energy intensity factors considered for data transfer.

	Energy intensity [kWh/GB]		
ICT infrastructure	low	typical	high
Radio access network (4G)	0.1 [52]	0.15 [24]	0.27 [24]
Metro and core network	0.01 [2]	0.06 [2]	0.08 [62]
Data centers and cloud	0.027 [1]	0.085 [1]	0.15 [65]

For the **deployment and decommissioning**, we consider three vehicles (trucks). In the case of the gateway, a low load factor (about 1%) is considered as the gateway is generally handled separately from the rest of the IoT nodes deployed per batch. The average distance per IoT node and gateway is based on an estimate as no data could be found. Similarly, because of a lack of data to properly model the **maintenance**, we consider the mean time between failures (MTBF) estimates for the IoT nodes and gateway provided by the company to capture the overhead in terms of hardware and transport. The impacts of data transfer for the regular over-the-air updates of the network are also taken into account.

Regarding the **end of life**, a very basic model was considered by assuming that electronic parts would end up in an incineration plant whereas plastic parts would end up in a landfill. The actual end-of-life management is clearly badly understood, even by the company itself. Unfortunately, this is a common observation in LCA of electronics: the end of life strongly suffers from a lack of data and considerations although this could have detrimental effects in categories such as ecotoxicity [53]. Consequently, our modeling most likely underestimates the actual end-of-life impacts.

4.3 Results and interpretation

The characterization and normalization results for the set of *typical* parameters are provided in Table 2. They are further broken down per life-cycle phases in Figure 3(a) for the full network as defined in the functional unit, and in Figures 3(b)-(c) for the IoT node and the gateway, respectively. The first conclusion is that the use phase is clearly dominating the environmental impacts (about 80%) for the majority of indicators, except for the T-EcoTox, T-Acid, HT-nc and ADP, where the production reaches at least 50%. This observation regarding the use phase is not surprising for IoT nodes powered directly by the grid as they usually have less power consumption constraints than battery-powered IoT nodes with a strict power budget [42, 43]. It also clearly appears in Figure 3(a) that the impacts generated by the IoT nodes are responsible for the highest share of the network, generally more than 90%.

The impacts of transport, deployment and decommissioning turn out to be extremely low compared to the other phases of the life cycle, mainly due to the very low weight of the products. Yet, Figure 3(c) shows the effect of a low load factor of vehicles for the gateway. Indeed, the deployment and decommissioning phases reach almost 20% of the impacts for some indicators whereas they were almost invisible in Figure 3(b). This points out the benefits of batch deployment as implemented for the IoT nodes.

The impacts of the data transfer from the gateway to the ICT infrastructure appear to be extremely low compared to the total impacts (less than 0.1%). This is mainly due to the very small amount of

Table 2: Characterization and normalization results for the functional unit over the impact categories considered in this study. The values are given for the *typical* set of parameters but the variation with respect to the *low* and *high* bounds are provided.

Impact category	Abbrev.	Charac.$^{\triangleleft}$	Units	Variability$^{\times}$[%] (w/o)	(w/)	Norm.$^{\triangleright}$[/]	CC Norm.*[/]
Climate change*,†	GWP	1642.9	$kgCO_2eq$	[−1; +3]	[−41; +176]	0.21	1.67-3.15
Primary energy demand$^{\diamond}$	PED	64233.6	MJ	[−0; +1]	[−45; +195]	-	-
Terrestrial ecotoxicity†	T-EcoTox	769.5	kg1,4-DBeq	[−3; +4]	[−20; + 77]	0.05	-
Terrestrial acidification†	T-Acid	2.0	$kgSO_2eq$	[−2; +6]	[−28; +121]	0.05	(0.02)
Photochemical ozone formation$^{\circ,\dagger}$	POF	2.1	$kgNO_xeq$	[−2; +7]	[−37; +160]	0.10	(1.53)
Land use†	LandUse	187.4	Annual crop.eq· y	[−1; +1]	[−47; +201]	0.03	0.15
Human toxicity, non-cancer†	HT-nc	59.9	kg1,4-DBeq	[−4; +7]	[−29; +117]	<0.01	(<0.01)
Human toxicity, cancer†	HT-c	0.9	kg1,4-DBeq	[−2; +2]	[−39; +169]	0.09	(0.01)
Freshwater eutrophication†	FE	<0.1	kgPeq	[−0; +2]	[−42; +180]	0.01	0.01
Freshwater ecotoxicity†	F-EcoTox	0.2	kg1,4 DBeq	[−2; +5]	[−37; +156]	0.01	(<0.01)
Freshwater consumption†	F-Water	13.2	m^3	[−0; +1]	[−43; +185]	0.05	(0.06)
Abiotic Depletion (ADP elements)‡	ADP	<0.1	kgSbeq	[−2; +10]	[−4; + 19]	0.31	0.63

◁ : characterization results ▷ : normalization results (typical), based on conventional normalization factors from ReCiPe† and CML‡
★ : carrying-capacity-based normalization results (typical), based on [9, 61]. Values in brackets were extrapolated by the authors
⋄ : renewable and non-ren. resources (net calorific value), from GaBi ∗ : excluding biogenic carbon (default) ° : human health
† : ReCiPe 2016 v1.1 Midpoint (H) ‡ : reserve base, from CML2001 - Aug. 2016
× : Variation for the *low* and *high* bounds. Ranges are provided without (w/o) and with (w/) the use phase variability, respectively

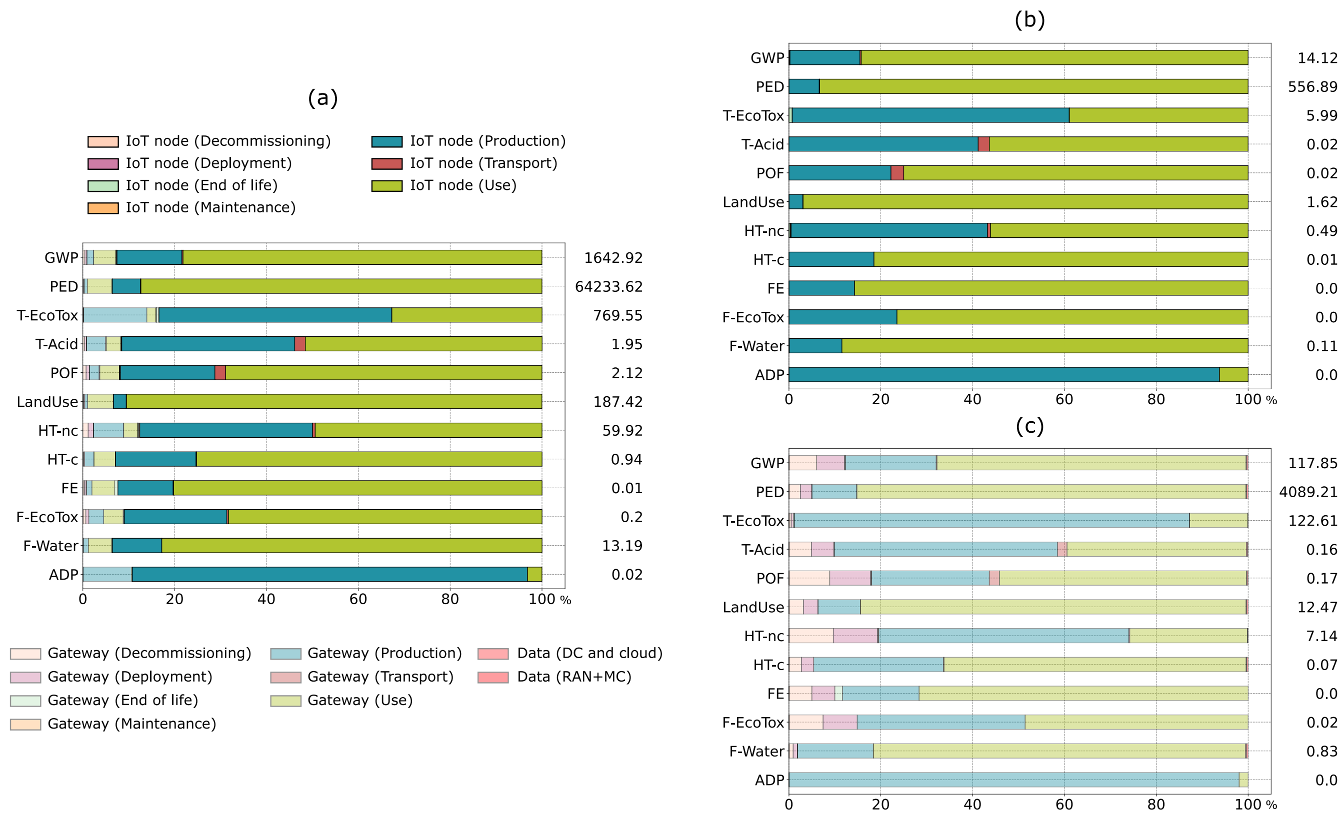

Figure 3: Breakdown of the characterization results per life-cycle phases for (a) the full network as defined in the functional unit, (b) a single IoT node, and (c) a single gateway. Units for each category are provided in Table 2.

data transmitted by the gateway. This conclusion cannot be generalized to all IoT systems as it strongly depends on the amount of data generated by the application as well as on the data management policy. It is worth to highlight the sober data traffic requirement of this solution, i.e., about 50 MB per gateway per month.

4.4 Discussion

Firstly, Table 2 shows that the variability between the *typical* and the *low* and *high* scenarios is significant when all variability is taken into account. In fact, most of the variability is associated with the use phase for which the variability is the largest. Nevertheless, by using knowledge from the company regarding the effective power consumption of their IoT devices, the variability is significantly decreased as shown in Table 2. In addition, several modeling iterations have been carried out to lower the modeling variability associated with the other life-cycle phases. We mainly used teardowns, hardware inspections, and interactions with the IoT company. For the majority of ICs, the exact silicon die area has been obtained through chemical desencaspulation, using the methodology detailed in [53]. This significantly reduces the variability regarding the modeling of ICs as the evaluation of the die area is often challenging [48, 53, 54, 65].

Secondly, the normalization results show that the environmental impacts of the IoT solution represent only a fraction of the traditional reference situations proposed by the ReCiPe and CML methods, which consider a world-average impact per person in 2010. However, these reference situations are not planetary-boundaries aware since "they are solely based on society's background interventions" but "cannot be used to compare the severity of these interventions in the ecosphere" [9]. In Table 2, we hence also propose carrying-capacity-based normalization results. With this other reference situation, we observe significant increases in normalized results for the GWP, the POF, the LandUse and the ADP. These increases can be explained by the fact that the carrying-capacity normalization factors per person per year are smaller in the context of planetary boundaries, e.g., for GWP, 522-985 $kgCO_2eq$ [9] rather than 7990.4 $kgCO_2eq$ with the ReCiPe method.

Lastly, the LCA results suggest that the most effective way to reduce the direct impacts of the IoT solution on indicators such as GWP and PED would be to reduce the use phase electricity consumption. However, this ecodesign suggestion is in contradiction with the economic incentives for the manufacturing company. We therefore conducted a streamlined life cycle costing (LCC) to estimate the economical costs of the production and use phases of the IoT solution, as depicted in Figure 4. This shows that the economical costs are mainly located on the production phase (more than 80%) whereas the environmental burden for indicators such as GWP and PED are clearly in the use phase, as shown in Section 4.3. As the company is selling the IoT solution to an operator who is managing the network of streetlights, optimizing the use phase will increase the financial costs for the company. On the contrary, the operator is not likely to complain about the electricity consumption of the IoT solution because it is much smaller than the expected energy savings per streetlight, as one lamp usually consumes between 80 and 120W. The company has therefore no direct economical incentive to reduce the environmental impacts of its current IoT solution. We also point out that the IoT solution under study is already a light-weight implementation of smart lighting, compared to real-time traffic counting solutions embedding edge-AI, cameras, and heavier data transfers [46]. Yet, the ecodesign of the IoT solution is still worth it as if the number of nodes deployed (i.e., the product throughput) is kept the same, reductions of absolute environmental impacts can be expected similarly to Figures 1(a)- (b). Nevertheless, if the ecodesign is used as a marketing argument to increase the number of deployed IoT nodes, this will (partially) cancel out the environmental savings, as foreseen by rebound mechanisms [25, 31].

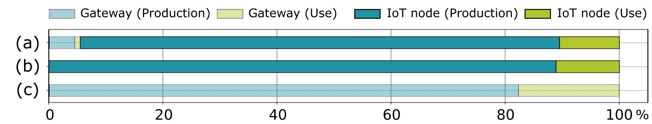

Figure 4: Streamlined life cycle costing results for (a) the full network as defined in the functional unit, (b) a single IoT node, and (c) a single gateway. Due to a lack of data on the entire life cycle, only economical costs due to production and use phase have been considered (bottom-up modeling).

This example undoubtedly illustrates the usefulness of LCA to improve the environmental performance of the IoT solution needed to implement the smart public lighting. However, this falls short from providing conclusions whether these gains are sufficient regarding environmental sustainability targets, such as planetary boundaries, or the Paris Agreement. A suggestion could be to modify the spatial and/or temporal goal and scope of the LCA to tackle this question, which we discuss in the next section.

5 TOWARDS BACKCASTING STUDIES FOR THE MASSIVE IOT DEPLOYMENT

Given that the question we are addressing aims at fostering that environmental limits will not be exceeded in the future, it naturally falls within the field of future studies [35]. Working on future scenarios from a sustainability perspective is clearly a nontrivial task [56], mainly due to (i) the inherent uncertainty about the future, (ii) the challenge of agreeing on a single definition of (environmental) sustainability, and (iii) the difficulty to capture complex system dynamics. About a decade ago, De Camillis et al. [18] investigated for the Joint Research Centre Institute for Environment and Sustainability (European Commission) the possibility to use LCA in future-oriented scenarios [22]. In this context, they discussed the use of attributional and consequential life cycle assessment [15, 18, 72]. The key difference between attributional and consequential LCA is that the former attempts to assess what environmental burdens can be associated with a product whereas the latter attempts to assess the environmental burdens that will occur, directly or indirectly, as a consequence of a decision [18]. Clearly, there is still ongoing debates in the LCA community regarding these two types of LCA [15, 72], hence calling for further research in this field. In our study, we could have used LCA and consider not only direct effects but also indirect effects. Yet, this would have required an important change in the functional unit of the study and a reformulation of its goal and scope to encompass not only the technological level (as it is typically done in conventional LCA), but also the application level. While this might have been feasible *in theory*, it has several limitations in practice, which make us favor another approach. First, the complexity associated with modeling the whole application level in LCA rapidly grows and becomes hard to handle. Then, this approach require a solid expertise in the advanced modeling principles of the consequential LCA methodology [29]. This could be an important limitation as even conventional LCA is far from being systematically conducted in the field of IoT [53]. Finally, dynamic LCA should be used to capture the temporal evolution of the numerous model parameters, adding on top of the aforementioned complexity. Therefore, we conclude that relying solely on the LCA methodology may bring an overall significant complexity.

5.1 Backcasting as a well-suited approach

Consequently, we propose to further investigate how LCA could be combined with future-oriented studies [22], as a part of a broader framework. The end-goal of this approach is to be able to discriminate between IoT solutions that would be relevant to be deployed and the ones that should be avoided or strongly discouraged with respect to environmental limits. Obviously, guaranteeing an absolute environmental sustainability is highly complex (if possible at all), regardless of the approach. Yet, in this section we explore several types of future-studies to identify a synergistic approach. Hence, we first define clearly the necessary features that should be fulfilled by the future study, namely:

- to be goal-oriented as we want to evaluate how to reach environmental targets;
- to integrate the quantitative inputs provided by the LCA results to model the direct environmental impacts;
- to allow for the integration of indirect effects [17, 41, 58];
- to consider a period of time spanning at least the period between today and 2030 or 2050, i.e., about 10-30 years;
- to capture spatio-temporal features specific to the territory;
- to be at least suited to environmental analysis, if possible complemented with socio-economic considerations;
- to be able to cope with important uncertainties without compromising the relevance of the analysis.

When analyzing the different methods existing to carry out future-oriented scenarios [22], three main types stand out, as categorized by [13], i.e., predictive (forecasts and what-if scenarios), explorative (external and strategic scenarios), or normative scenarios (preserving or transforming). They respectively target the questions: "what will happen?", "what can happen?", and "how can a specific target be reached?" [22]. The most suitable method with respect to the set of features previously defined turns out to be the normative scenario in the transformative perspective given the long-term period and the nature of the changes introduced by the IoT solutions. This type of future study is also called *backcasting*, as introduced in the 1990s by John Robinson [59]. The backcasting methodology is intended for scenario analysis of changes occurring over 20 to 100 years in the future and is particularly well-suited to goal-oriented studies as it consists in defining a vision of a desirable future and then working *backwards* from the end-point vision to the present [6, 59]. The key characteristic of backcasting compared to predictive forecasting techniques is to focus on *how* desirable futures can be attained, rather than predicting what futures are likely to happen [59]. Although this difference may seem marginal at first sight, we argue that it is an important paradigm shift from the conventional forecasting approach in ICT. In fact, similarly to what is pointed out in [21], backcasting could help us to "break away from default modes of thinking" and "think beyond established technological lock-ins and the path-dependence that follows from decisions that might have been taken decades ago". *Backcasts* should hence help determining the physical feasibility of a desired future and the implications in terms of policy measures.

Recent studies consider the use of backcasting in the context of smart city [6, 20], but they remain qualitative and do not integrate quantitative scenarios. Yet, Robinson pointed out the need to include impact assessment in the backcasting [59], although it has been the most neglected aspect so far [22, 59]. Nevertheless, LCA modeling approach for backcasting scenario assessments has a very low maturity in practice, with almost no endorsement or testing [18]. Although this generally confirms that LCA and backcasting could be complementary, explorative work is clearly needed. This study hence attempt to take a first step in this direction by using the in-depth evaluation of the direct impacts of the IoT smart layer in a backcasting scenario applied to smart public lighting.

5.2 Streamlined backcasting on the use case of smart public lighting

In this section, we propose a streamlined pass through the different steps of the backcasting method, as detailed in [59]. However, we cannot perform a fully quantitative backcast because we are lacking key information from field players (i.e., operators, municipalities, ...) to provide specific and realistic quantitative values. Nevertheless, we carry out a *streamlined backcast* and we define scenarios based on public reports and scientific literature to illustrate the potential of backcasting. However, the results remain conceptual. This means that we should not draw final conclusions on the relevance of IoT for our use case, but rather exemplify what kind of results could be provided by a backcasting approach.

Step 1: Determine objectives

The purpose of this analysis is to understand if and how the deployment of an IoT solution for smart public lighting could help to meet the Paris Agreement (PA) target of 1.5°C. This is somehow very similar to the "Carbon Law" approach followed in [50, 60], although the application is very different. Moreover, Robinson [59] explicitly mentioned environmental targets as a strong driver for backcasting. We focus on the Walloon Region (Wallonia) in Belgium at the horizon of 2050 in order to anchor the backcast in a well-defined spatio-temporal context. The use of national or sub-national scale for backcasting is aligned with recommendations provided in [18], as the spatial boundaries correspond to political jurisdictions [59].

Step 2: Specify goals, constraints and targets

The type of desirable future society envisioned for the backcast is chosen to be "a world in line with planetary boundaries in 2050

Table 3: Definition of the scenarios for the backcasting.

Scenario	Description	Comment
Baseline		
No action	Current infrastructure with an electricity mix decarbonization of 0.8%/year† [67]	No action
Replacement with LED	Linear replacement of all streetlights with energy-efficient LED lamps by 2030	Already planned
Non-technological		
Shutdown	Current infrastructure with shutdown during 40% of the night time from 2022 to 2050	Inspired by recent shutdown
Smart		
Smart w/o IoT effects	Dynamic remote dimming and predictive maintenance (smart lighting without IoT effects)	Technological (IoT)
Smart w/ IoT direct effects	Dynamic remote dimming and predictive maintenance (direct effects included)	Technological (IoT)
Smart w/ IoT effects	(Conceptual) Modeling of indirect and structural effects on top of Smart w/ direct effects	Socio-technological (IoT)

† : the effect of electricity mix decarbonation (*exogenous variable*) is not taken into account in the other scenarios

(and after)". This is then narrowed down to "Wallonia in line with the Paris Agreement target of no more than 1.5°C by 2050" [47, 67]. Note that we could also have considered the 2°C target, or even the "Plan Air Climat Energie (PACE) 2030" [27] issued by the Walloon Region. The question of how to allocate the global remaining carbon budget between activity sectors and between countries to comply with the Paris Agreement is non trivial and subject to important inequalities [8]. In PACE 2030, local authorities allocated GHG reductions for each sector. For instance, the tertiary sector (relevant for the public lighting) has been assigned a reduction of 63% for 2030 compared to 2005 [27]. In comparison, observed reductions in this sector from 2005 to 2019 were evaluated only at about 11%.

Step 3: Describe the present system
The current public lighting system in Wallonia gathers more than 600 thousand streetlights [66], which is estimated to consume at least 130 GWh in 2019, or about 1% of the total electricity of Wallonia [70]. If we consider a carbon intensity of 0.19 $kgCO_2eq/kWh$ for the electricity [49], this yields about 25 $ktCO_2eq$ in 2019. Local authorities have already planned to replace all the halogen streetlights with energy-efficient LED lamps by 2030 in order to reduce the costs of public lighting [26]. The existence of this plan highlights the importance of focusing on a national or sub-national scale [18].

Step 4: Specify exogenous variables
Exogenous variables are variables that are not included within the backcast itself but that must be specified for the backcast to be carried out [59]. A concrete example would be the improvements regarding the carbon intensity of electricity production in Belgium. We do not consider modifications in the impact of economic growth and population growth in the backcast and we assume the socio-economic system to be stable under the period of study. This could be discussed, but we leave it outside of the scope of this backcast.

Step 5: Undertake the scenario analysis
Several scenarios are listed in Table 3 in order to show the diversity of scenarios that could be investigated for backcasting. These scenarios aim at considering both technological and non-technological evolutions that can be implemented by a change in behavior or policy. For instance, due to the steep increase of energy prices during the end of 2022, several municipalities decided to shut down public lights at night to reduce the electricity consumption and hence

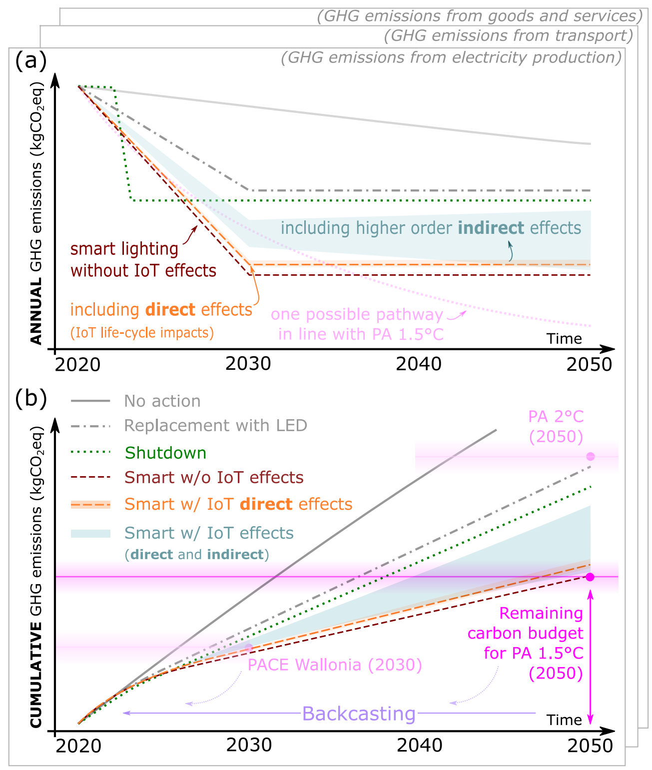

Figure 5: Conceptual results of the streamlined backcasting study for (a) the annual GHG emissions, and (b) the cumulative GHG emissions. For the public lightning, the backcast consider only GHG emissions from electricity consumption.

the energy costs [40]. In futures of scarcity, we could therefore imagine a partial shutdown of streetlights in the long term in a non-technological *Shotdown* scenario, although this can generate other issues, e.g., in terms of safety. The *No action* scenario considers that the current lighting infrastructure will be kept, and we illustrate the effect of a modification in exogenous variables through a decarbonation of the energy mix. Then, we consider IoT *smart* scenarios that implement dynamic remote dimming of lights, which offers more flexibility and extra energy savings [51]. Dimming schemes reported in the literature enable power savings of 15 to 40% for the lights [51], and this could go up to 60% according to the company. *Smart w/o IoT effects* and *Smart w/ IoT direct effects* scenarios differ by the inclusion of the IoT direct effects whereas *Smart w/ IoT effects* conceptually adds modeling of indirect and structural effects, including rebound effects. Indeed, as stated in [56], "taking into account all these effects extensively is extremely difficult (if not impossible)".

Step 6: Undertake the impact analysis
The results presented in Figure 5 are conceptual results of the streamlined backcasting. First, this highlights the importance of focusing on the cumulative emissions rather than on exclusively on the pathways. In fact, the cumulative nature of GHG emissions in the atmosphere yields remaining carbon budgets for +1.5°C and +2°C, as explained in IPCC reports [38, 47]. Then, although the replacement of the lightning infrastructure with energy-efficient LED lamps is effectively decreasing the GHG emissions, this is far from being sufficient to fulfill the Paris Agreement. Moreover, given the delay introduced by the deployment of a technology, the system inertia should be systematically taken into account in the context of climate change [64]. Indeed, the longer we wait for GHG reductions, the faster we will need to reduce our emissions [50]. The non-technological scenario shows that a partial shutdown of public lighting (40% of the time) has the advantage to quickly reduce GHG emissions. However, Figure 5(b) shows that this falls short from meeting the target on the long term. The *Smart* scenarios depict important energy savings, which turns into significant GHG reductions. Yet even the *Smart* scenario without direct and indirect effects of the IoT is close to exceed the carbon budget around 2050. Moreover, it assumes a massive deployment starting in 2020, which is clearly optimistic. The second *Smart* scenario includes the results of the LCA (with its variability), hence worsening the situation. Finally, the *Smart* scenario with both direct and indirect effects gathers several higher order effects to provide an overview of what a comprehensive quantitative backcast could look like, e.g., rebound effects capturing an increase in the number of streetlights, GHG emissions associated with the production of new streetlights, more complex IoT solution with edge sensing which enables further energy savings, etc. This last scenario shows that even with important uncertainty, backcasting could still be useful to discriminate between scenarios that are largely insufficient, and those that might be suitable options.

5.3 Discussion

It is important to realize that a quantitative analysis tends to narrow down a complex problem to a small set of indicators capturing only a part of the overall problem [28]. For instance, our backcast focuses only on the carbon footprint as quantitative targets are explicitly defined at the horizon of 2050. If deploying IoT solutions may help in some cases to mitigate GHG emissions, it will increase the consumption of abiotic resources [42] and increase the quantity of e-waste [37]. Moreover, our backcast focuses on the GHG emissions caused by electricity consumption, but the same approach should be carried out for the GHG emissions related to transport as the maintenance of the public lights undoubtedly entails a displacement of technicians and vehicles. The lack of suitable real-life data can be particularly problematic in the context of backcasting, as already pointed out in [59]. This would require integrated research to better capture higher order effects, even with large uncertainty. A comprehensive backcasting could also include economical and social considerations. For instance, the use of IoT solutions can create geopolitical dependencies as the majority of electronics is currently not produced in Europe. Finally, the need and relevance of quantitative scenarios could be questioned, especially because of the inherent uncertainty and several socio-economic factors affecting the study. Nevertheless, the main advantages of quantitative backcasting studies to deal with environmental limits [22] is (i) to help identifying the factors that are crucial to reach the target, (ii) to rapidly identify scenarios that would not be sufficient enough to reach the target, and (iii) to better communicate on the order of magnitude for the changes required. In other words, this can be a way to systematically put reductions in perspective with global strategies and targets based on solid foundation from the environmental sciences, which was pointed out by Rasoldier et al. [56] as a lack in the literature.

6 CONCLUSIONS AND FUTURE WORKS

Since a few decades, the development of technologies is moving forward at a frantic rate. Emerging technologies such as IoT are strongly orienting innovation in academia and industry, supported by significant financial investments and policies [45]. Although such technologies are theoretically aiming at putting our developed societies on tracks towards less resource intensive patterns, the actual socio-technical system is generally moving further away from a state of environmental sustainability [8, 38, 64]. Moreover, environmental concerns have been raised due to the ongoing massive deployment of IoT devices [23, 53]. In this study, we hence investigated what strategy should be used to help keeping IoT deployment within environmental limits. We first argued that conventional LCA are not sufficient to guarantee environmental sustainability, hence calling for a broader framework. Then, we showed that backcasting scenarios have the potential to effectively help understanding *if*, and most importantly, *how* IoT could help to meet GHG reduction pathways, contrary to traditional forecasting studies in the field of ICT. In particular, we argue that backcasting could be a realistic approach to "imagine and propose credible, preferable, and evocative alternatives" [21] in line with environmental limits. We illustrate this with the case study of smart public lighting in Wallonia, Belgium and we carry out a full-scope gradle-to-grave and multi-indicator LCA to assess the environmental impacts of this real-life IoT solution. We hope this paper will stimulate future research to work on the synergies between LCA and backcasting in the field of ICT and IoT, while combining the advantages of quantitative analyses with necessary qualitative considerations.

ACKNOWLEDGMENTS

The authors thank the company for the fruitful inputs and discussions, and for allowing open-source publication which is not a common practice. The authors are also very grateful to the UCLouvain ECS group members for their unveiling proofreading and discussions. This work was supported by the Fonds européen de développement régional (FEDER) and the Wallonia within the Wallonie-2020.EU program.

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A APPENDICES

This supplementary material provides additional details regarding the LCA modeling carried out in this study. For more details, please feel free to contact the authors.

A.1 Topology of the site using the smart public lighting solution

Figure 6 shows a schematic map of the site where the smart public lighting solution is deployed. The public road in green highlights the portion equipped with the IoT solution.

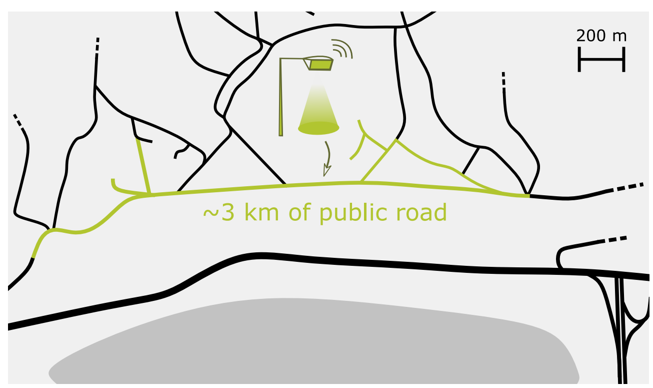

Figure 6: Schematic map of the deployment site.

A.2 Simplified bill of materials

The complete bill of materials (BoMs) for the gateway and the IoT node contains each more than 70 entries, with one entry representing a different type of component or module. As a module can also gather up to several tens of components, the comprehensive BoMs are very long. Table 4 and Table 5 provide highly simplified versions of the BoMs, structured according to the functional blocks proposed in [53] to ease readability.

Table 4: Simplified bill of materials for the gateway.

Functional block	Components	Modeling based on ...	Physical quantity
Actuators			
	-	-	-
Casing			
	Housing	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.37 [kg]
	Screws, fasterners and nuts	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.22 [kg]
Connectivity			
	Bluetooth Low Energy Stand-alone (NINA-B301-00B)	In-depth custom modeling in Sphera LCA	1
	Wifi USB dongle (Edimax)	In-depth custom modeling in Sphera LCA	1
	Modem cellulaire PCIe (EG25GGB-MINIPCIE)	In-depth custom modeling in Sphera LCA	1
Memory			
	IC (Flash, microSD Card 16 GB)	"WLP CSP 196 (400mg) (12x12x1.41mm) flash (45 nm node)" in Sphera LCA	1
Others			
	Capacitors	"Capacitor ceramic MLCC 0603 with base metals (6mg) 1.6x0.8x0.8" in Sphera LCA	28
	Capacitors (Tantalum)	"Capacitor tantal SMD E (500mg) 7.3x4.3x4.1" in Sphera LCA	3
	Resistors	"Resistor flat chip 0402 (0.6mg)" in Sphera LCA	40
	Diodes	"Diode signal DO214/219 (14.8mg) 3.9x1.9x1" in Sphera LCA	2
	EMS shield	"EMS shielding" in Sphera LCA	0.003 [kg]
	Solder paste	"SnAg3Cu0.5 (SAC-Lot)" in Sphera LCA	0.000698 [kg]
	Fuses	**Not modeled**	-
	Connectors	**Not modeled**	-
PCB			
	Antenna Patch GPS	"Printed wiring board, rigid, FR4, HASL, 2-layer"	0.00056 [m^2]
	Antenna Patch 4G LTE	"Printed wiring board, rigid, FR4, HASL, 2-layer"	0.0016 [m^2]
	Assembly line	"Assembly line THT/SMD (1TP,1SP,1CS,1WO,1Rf) throughput 600/h" in Sphera LCA	-
	Main PCB	"Printed Wiring Board 4-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.0186 [m^2]
	Custom antenna PCB	"Printed Wiring Board 2-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.000182 [m^2]
Power supply			
	Toroidal choke	"Ring Core Coil 8g (Without housing)" in Sphera LCA	1
	ICs, LDO, and transistors	BGA, SOT, and D2PAK ICs in Sphera LCA	Several
Processing			
	Raspberry Pi (model B)	In-depth custom modeling in Sphera LCA	1
Security			
	-	-	-
Sensing			
	-	-	-
User Interface			
	LEDs	"Piece of LED top SMD (35mg) 3.2x2.8x1.9" in Sphera LCA	4
	Light pipe	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.000264 [kg]

Table 5: Simplified bill of materials for the IoT node.

Functional block	Components	Modeling based on ...	Physical quantity
Actuators			
	-	-	-
Casing			
	Housing	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.051 [kg]
Connectivity			
	Bluetooth Low Energy Stand-alone (NINA-B301-00B)	In-depth custom modeling in Sphera LCA	1
	GPS Module, Ultra Compact (L80-M39)	In-depth custom modeling in Sphera LCA	1
Memory			
	IC (Flash)	"IC TSSOP 16 (59mg) 4.4x5.0 mm flash (45 nm node)" in Sphera LCA	1
Others			
	Capacitors	"Capacitor ceramic MLCC 0603 with base metals (6mg) 1.6x0.8x0.8" in Sphera LCA	36
	Resistors	"Resistor flat chip 0402 (0.6mg)" in Sphera LCA	47
	Inductors	"Coil multilayer chip 0402 (1mg) 1x0.5x0.5" (likely underestimated)	1
	Diodes	"Diode signal DO214/219 (14.8mg) 3.9x1.9x1" in Sphera LCA	3
	EMS shield	"EMS shielding" in Sphera LCA	0.0005 [kg]
	Solder paste	"SnAg3Cu0.5 (SAC-Lot)" in Sphera LCA	0.00014 [kg]
	Fuses	**Not modeled**	-
	Connectors	**Not modeled**	-
PCB			
	Main PCB	"Printed Wiring Board 4-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.0036 [m^2]
	Custom antenna PCB	"Printed Wiring Board 2-layer rigid FR4 with chem-elec AuNi finish" in Sphera LCA	0.000182 [m^2]
	Assembly line	"Assembly line THT/SMD (1TP,1SP,1CS,1WO,1Rf) throughput 600/h" in Sphera LCA	-
Power supply			
	Diodes	"Diode power DO214/219 (93mg) 4.3x3.6x2.3"	2
	Power inductors	"Coil miniature wound SDR0302 (81mg) D3x2.5"	1
	ICs, LDO, and transistors	SOT ICs in Sphera LCA	Several
Processing			
	-	-	-
Security			
	-	-	-
Sensing			
	3-Axis Digital MEMS Accelerometer	"IC DIP 8 (538mg) 10.9x6.6 mm CMOS logic (250 nm node)" in Sphera LCA	1
	Lux meter	"IC DIP 8 (538mg) 10.9x6.6 mm CMOS logic (250 nm node)" in Sphera LCA	1
User Interface			
	LEDs	"LED top SMD (35mg) 3.2x2.8x1.9"	2
	LED	"Piece of LED top SMD (35mg) 3.2x2.8x1.9" in Sphera LCA	4
	Light pipe	Custom modeling in Sphera LCA based on polycarbonate (PC) granulate	0.000264 [kg]