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► **To cite this version:**

Clément Morand, Jacques Combaz, Aurélie Névéol, Anne-Laure Ligozat. When rebound effect is not a side effect: analyzing sociotechnical contexts of digital technologies. 2026. <hal-05566029>

HAL Id: hal-05566029

<https://hal.science/hal-05566029v1>

Preprint submitted on 25 Mar 2026

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Highlights

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- Rebound effect can be inadequate to describe environmental dynamics of ICT
- Analyzing sociotechnical contexts helps detail the consequences of energy efficiency
- Energy efficiency is an intended enabler of growth of activity in our case studies

When rebound effect is not a side effect: analyzing sociotechnical contexts of digital technologies

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Abstract

Digital technologies are often presented as great sources of efficiency. They however also cause significant environmental damages. Rebound effect is defined as efficiency gains leading to increased resource use. Its role in the environmental impact of digital technologies remains unclear because it is unknown whether the environmental impacts raise *because of* or *in spite of* the efficiency gains. This dynamics is often explored by relating efficiency gains to changes in demand following an economic perspective.

Stakeholders leverage energy efficiency along other technical changes as parts of their development strategies. Accounting for the sociotechnical contexts of technological developments is therefore instrumental to understand environmental impacts dynamics.

In this paper, we analyze the sociotechnical context of two case studies: the roll-out of 5G in France, and, deep learning model training. We identify technical characteristics and actors intentions to clarify the role energy efficiency plays in these technological developments and their (environmental) consequences.

In both cases, major actors openly show intent towards activity growth. Energy efficiency serves as one of the levers to achieve their goal. The concept

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of rebound effect thus seems inadequate to capture the dynamics at play in our case studies. Indeed, energy efficiency is not used (principally) to reduce impact, but rather to allow for the creation of new uses.

We believe that similar conclusions could be obtained on numerous other aspects of digitalization by using our methodological framework. Our results suggest rethinking the framing of energy efficiency to better approach the environmental consequences of digitalization.

Keywords: Rebound effect, Digitalization, Environmental impacts, Machine learning training, 5G, Energy efficiency

1. Introduction

Information and Communication Technologies (ICTs) are often framed as a key lever towards environmental sustainability because of potential efficiency gains they are expected to bring. *Twin transitions* [13] explore how ICT development can help in decoupling economic growth from environmental damages to achieve sustainability. However, benefits are not straightforward as ICTs also cause environmental damages [194, 70].

The environmental trajectory of ICTs is difficult to comprehend as growing deployment occurs at the same time as significant increased efficiency. Koomey's law illustrates this through the historical trend of exponentially increasing amount of compute per joule over the years while compute demand also raises. This phenomenon is understood under the framing of *rebound effects* [50, 29, 82], i.e. optimizations reduce the unitary impacts but lead to increased units thereby voiding the gains from the optimizations. Controlling rebound effects seems instrumental to understand and mitigate the environmental impacts of ICT.

Framing environmental dynamics of ICTs as a matter rebound effects boils down to determining whether the environmental impacts raise *because of* or *in spite of* the efficiency gains. This dynamics is often explored by relating efficiency gains to changes in demand following an economic perspective, focusing on price effects, as we show in Section 2.

Digital technologies are the product of a specific sociotechnical context. We thus claim that their development and environmental effects cannot be fully understood without considering this context. Isolating the sole effect of efficiency gains seems highly difficult and anyway irrelevant since technical features of digital technologies are often interdependent or bundled [82, 72]. Rebound effects are often overlooked in environmental assessments of ICT, which focus on impact reduction potential and fail to evaluate negative consequences of ICT deployment [23, 25, 148, 121, 145]. It is likely that this is due to the difficulty to understand dynamics at play solely based on the technical aspects.

In this article, we investigate how understanding the socioeconomic context around ICT deployment can help understanding the ICT environmental impacts dynamics. In two case studies, the roll-out of 5G in France and deep learning model training, we analyze the sociotechnical deployment context, technical characteristics and stakeholder intentions to show the role energy efficiency plays in these technological developments and their environmental consequences.

The main contributions of this work are as follows:

- We propose a methodological framework to describe the sociotechnical context around energy efficiency in ICT.
- We apply our framework on two case studies: 5G deployment in France and deep learning model training. We show that stakeholders aim at increasing activity and leverage energy efficiency to that end.
- We demonstrate that the framing of rebound effect fails to capture the dynamics at play in our case studies.

2. A literature review on rebound effects

2.1. A brief history of the “rebound effect”

After the 1970s energy crises, some governments introduced energy conservation programs including mandated efficiency standards for consumer products. Energy economists debated the policies’ cost-effectiveness, expressing radically different

opinions [20]. Khazzoom and Brookes independently questioned the value of the policies [113, 114, 115, 35, 36, 37, 38] arguing that the energy savings reported by “*conservationists*” were fallacious, largely overestimated because they were not including the effect of energy efficiency on energy demand, initially called “*economic effect*,” “*price effect*,” or “*feedback effect*” [113, 114].

Khazzoom and Brookes even suggested that conservation policies were counterproductive, leading to increase energy consumption instead of any reduction, the so-called “*backfire*” [113] also referred to as “*Khazzoom-Brookes postulate*” [159] or “*Jevons’ paradox*” [4]. Khazzoom’s position used microeconomic arguments and Brookes’ was supported by macroeconomics. Most of those were already in Jevons’ book about exhaustion of coal in Britain published in the beginning of Industrial revolution [111, 130], but his work had fallen into oblivion ever since, as Khazzoom and Brookes quickly realized after their first publications. Khazzoom and Brookes sparked a controversy among energy economists: Khazzoom faced Lovins in the 1980s over energy-demand reduction in *The Energy Journal*, and Brookes confronted Grubb in the 1990s over GHG emission reduction in *Energy Policy* journal. The term “*rebound effect*” was introduced by Lovins in his first reply to Khazzoom [122], and then reused by Grubb to counter Brookes and minimize the importance of the effect by denying its novelty [86, 37]. In fact, the term was already being used at the time by some energy experts [20, 72].

Debates relied on neoclassical economics to address theoretical [113, 114, 99, 159] and empirical [165, 166, 83] aspects of rebound effects. The existence of rebounds was widely accepted, but their magnitude (often estimated with price elasticities [176]) and underlying causes and effects [100], were sources of disagreements. Greenhalgh, for example, believed that energy efficiency, among other factors, played an important role in the demand for energy services [83], whereas for Lovins explanations lay elsewhere [122]. Brookes’ opponents also retorted that “*naturally occurring energy efficiency improvements*” observed historically tend to focus on the areas they are economically profitable, probably leading to substantial rebound effects, as opposed to targeted efficiency improvements found in policy-driven conservation programs [83, 86].

The term “*rebound effect*” eventually became established in energy economics debates following the special issue 6–7 of Energy Policy 28 in 2000, in which the phenomenon was further studied and the first taxonomies of rebound effects were produced [1, 19]. Defined as the “*interaction of energy use with the efficiency of energy use*” [160, 161, 28] and explained by the “*behavioral response by the economic agents*” [19], the effect was described as both “*perverse*” since it went against energy conservation [28], and “*so obvious*” since it was foreseen by basic economics [160].

The contribution of Sanne, a Swedish sociologist, stands out in the Energy Policy special issue otherwise dominated by neoclassical economics. He extended the definition of rebound to “*the overall effects of technical, organisational and social progress which increases the efficiency of the economy and give room for more consumption*” [153]. Schneider et al. refined this definition by linking rebounds to the “*reduction of limits to use a technology[, t]hese limits might be monetary, temporal, social, physical, linked to efforts, spatial or organisational*” [164], shifting the burden of proof: To avoid rebound, something must limit consumption growth, which can be market saturation. Both Sanne and Schneider critique the consumption- and growth-driven socioeconomic model and highlight the contradictions between economic goals and ecological limits. They purport that rebound effects are driven primarily by the context rather than by efficiency gains themselves.

In the 2000s, ecological economics, industrial ecology, and broader sustainability science entered the rebound-effects debate [157, 129]. The concept of rebound effects was extended to other resources besides energy [129]. Binswanger [26], Jalas [109] explored its temporal dimension and Hertwich [102] other categories of environmental impacts besides climate change. It is also a central concept of the literature on environmental impacts of ICTs from the very first publications, e.g. [104, 17, 143, 205].

There is currently no consensual definition of rebound effects [41, 5]. Most definitions are limited to technical efficiency improvements, unlike the propositions of Sanne and Schneider. They usually refer to the “*potential*” savings from

efficiency gains, calculated assuming that efficiency and demand are independent. The rebound effect occurs when part, or even all in the case of “*backfire*,” of these theoretical savings are not realized in practice, in particular due to economic mechanisms¹. Thus the rebound effect is seen as a force counteracting efficiency gains². It is also often described as an “*unintended*,”³ “*negative*,”⁴ “*secondary*”⁵ or “*side-effect*”⁶ from efficiency improvements.

The literature generally distinguishes *direct* rebound effects, i.e., when the savings are offset by an increase in demand for the good or service whose efficiency is improved, from *indirect* effects related to reallocation of those savings to other products. Besides these microeconomic effects, *economy-wide* effects are additional consequences of energy efficiency gains propagating throughout the economy, e.g. due to interconnected markets or to macroeconomic mechanisms [55, 176, 158].

2.2. Criticisms of rebound effect

Intention. Even though rebound effect is often seen as an “*unintended side-effect*” [150, 173, 67, 144, 117], the concept has been applied to situations in which global reduction of energy or resource consumption, or environmental impacts, was not the goal pursued to improve efficiency, starting with the paradigmatic case of the improvements of the steam engine brought by Watt during the Industrial revolution. For Watt and his business partner Boulton, it was a matter of making profits from the sales of steam engines, not to reduce the global coal demand in the UK, as evidenced by the numerous patents they filed and this famous quote from Boulton: “*I sell here, sir, what all the world desires to have—POWER.*”

Characterizing the rebound effect as “*unintended*” is not universally accepted [5],

¹See e.g. [122, 4, 175, 174, 110, 54, 44, 181, 182, 12, 68, 127, 137, 75, 197, 149, 50, 58, 104, 73, 119, 118, 129, 117, 95].

²This can be found in e.g. [102, 28, 104, 17, 18, 146, 156, 51, 16, 34].

³See e.g. [206, 102, 189, 151, 56, 68, 150, 173, 52, 129, 67, 144, 117, 5, 95, 84, 123, 43].

⁴See e.g. [102, 105, 151, 41, 82, 106, 127, 185, 50, 129, 5].

⁵See [102, 69].

⁶See [102, 82, 185, 156, 150, 173, 144, 201, 117].

some academics suggest that the effect is often voluntary, linked to economic goals in a context of growth and competition [162, 163, 204, 137, 73]. Such specific cases are called “*intended rebound effect*” by Williams et al. [201], “*rebound-inducing action*” by Galvin [73] and “*induction effects*”⁷ by Røpke [151] and Cano and March [43]. Note that this topic was already discussed in the 1990s when Grubb distinguished between energy efficiency as a “*goal*” and as a “*means*” [86].

Contradictions between economic and ecological goals. Intentionally provoked rebound effects should not be considered paradoxical, as many authors emphasize that they are in fact positive from an economic perspective [99, 38, 28, 30, 187, 87, 45, 31, 137, 77, 197, 67, 34], part of “*normal*” economic life [101, 134, 137]. Rebound effects becomes problematic only when examined from an environmental perspective [137], explaining why it is generally considered as “*negative*” in sustainability sciences. Although this tension between economic and ecological goals has been raised by several authors [153, 164, 162, 163, 82, 137, 150, 67], this topic is seldom addressed, perhaps because sustainable development, intended to reconcile economic development and social and environmental issues, is the dominant paradigm.

Reductionist approaches. Causality links between efficiency and demand are at the heart of rebound debates [100]. They are typically evaluated in isolation from other aspects [126, 154, 127, 77, 118] and from a microeconomic perspective, often focused on consumer demand [110, 75, 158, 197, 149, 73]. However, establishing simple, direct, indisputable links seems vain considering the complexity of the socioeconomic mechanisms at stake. Some authors acknowledge this “*cause-effect relativity*” [154, 158] and suggest to go beyond “*mechanistic*” [73] views of rebound effects, recognizing the complex human-material arrangements within which social practices take place [75]. They see energy efficiency as an

⁷Note that this term can take other meanings in the literature: see [104, 105, 146, 41, 96, 106, 24, 117].

“*enabler*” [173, 204, 76] of rebounds rather than a “*necessary and sufficient cause*” [158], and highlight the importance of the context [153, 162, 163, 204, 137] and the role of specific economic agents [73].

The notion of “*functional equivalence*”, allowing comparisons of services and on which energy efficiency or more generally eco-efficiency are based, has also been criticized for being a “*simplistic analytical tool*” for framing environmental issues that allows to “*remain within the comfort zone of reductionist science*” [76]. It also appears inappropriate for the specific case of ICTs [104, 105, 54] as they are chosen “*precisely because they are different, not functionally equivalent*” [146].

Conclusion. The dominant interpretation of the term “*rebound effect*” stems from the context in which it was coined. At the time energy savings were genuinely intended by conservation policies and occasionally observed and taken back after a while [114], justifying a definition of the rebound effect as the deviation between potential and actual savings. However, as we have shown the concept has been applied well outside this original scope.

Over time the rebound effect was a support for very different criticisms and positions [55]. For “*conservationists*” Lovins and Grubb, sustainability is compatible with maintaining economic growth [88], provided massive investments are made in “*resource efficiency*” [195]. By contrast, for Khazzoom, Brookes, and Greenhalgh, there is no “*free lunch*,” i.e. energy conservation and compliance with climate targets are unavoidably associated with economic costs [39]. However, they do not necessarily imply that growth should be withdrawn. For example, Khazzoom was skeptical about the necessity of climate mitigation [36, 39] and an advocate for the free market like Greenhalgh and Jevons. With the integration of sustainability sciences in the 2000s, the rebound effect has become an argument for questioning growth and green growth objectives [153, 162, 163, 73, 204, 137, 150, 149, 58, 140, 155].

3. Methodology

The standard framing of rebound effects attempts to isolate a single technical feature, typically energy efficiency, as cause of outcomes. We argue impacts arise from multiple intertwined technical characteristics interacting within specific sociotechnical contexts. Technologies are produced by stakeholders in specific sociotechnical contexts. We thus claim that analyzing stakeholders' strategies and the interplay between technical features is essential to understand potential effects in ICT deployment.

The two following subsections present an analytical framework to integrate these insights into our practical case studies.

3.1. Characterizing how energy efficiency relates to other technical aspects

Technologies have multiple technical characteristics in addition to energy efficiency. For instance 5G is more energy efficient than 4G, but also brings higher data rates and shorter delays. The combination of these different technical aspects, through different interactions between them, creates specific potentialities, i.e. effects that could happen depending on the deployment context. Understanding potentialities of energy efficiency thus requires studying the relations it has with other aspects of the technology. Analyzing the individual and combined potentialities of these technical characteristics is the first ingredient of the proposed framework.

3.2. Analyzing the interactions between technical features and stakeholders deployment strategies

Rebound effect was initially introduced for assessing energy consumption reduction policies and later extended to environmental impacts assessments. ICT for sustainability communities often frame rebound effect as a risk to be addressed so that an optimization effectively leads to a net decrease in environmental impacts. The matrix of impacts proposed by Hilty and Aebischer [106] for instance posits that optimization and substitution effects are positive for environmental sustainability, while rebound is a negative impact. Section 2

shows that, in contrast, rebound effect can also be conceptualised as a form of economic law, desirable from an economic perspective. In any case the labeling “rebound” “effects” creates a *causal* narrative: an optimization is first introduced, then, demand increases.

We argue that the causal narrative of rebound is often reversed. Expected or observed increase in demand often drives the adoption of optimisations to enable or trigger higher demand. In this situation, the resulting increase is intentional and represents a success, as opposed to (unindented) rebound effects which typically apply when the goal is to cut environmental impacts. Williams et al. [201] calls these “*intended rebound effects*”, while Schneider [162] proposes to frame them as “*rebound strategies*” “*removing limits to increased consumption*”. Recognizing cases of reversed causality clarifies when efficiency is an increased activity driver rather than a sustainability tool.

Whether there is an intention to cut impact or simply to boost performance shapes the deployment context, the technology features, and its usage patterns. When impact reduction is a goal, designers avoid features that encourage overuse or may even take measures to prevent unintended demand growth. When the primary objective is expansion, the technology often includes features that actively encourage increased use. Consequently, understanding of the intention and motivations behind ICT development and deployment is highly valuable to environmental assessments.

Following Galvin [73], we propose to bring the different actors behind energy efficiency to the forefront. We thus want to account for their motivations and the tactics they deploy to attain their goals. This process in turn allows to better understand the different dynamics around energy efficiency.

Focusing on actors’ intentions clarifies how their stance on sustainability or energy efficiency influences ICT production, consumption, and overall environmental impact. We investigate whether and how these goals are integrated and prioritized alongside other objectives. This allows us to distinguish genuine efforts toward sustainability from incidental, pleasant side-effects of other tactics.

Indeed, ICT deployment is often associated with contexts of economic growth [40,

Chapter 1] where actors might engage in *growth policies* that must overcome short or long term limits to growth [162]. Identifying the limits actors attempt to push clarifies their intentions and reveals how levers such as efficiency are strategically used to meet goals.

3.3. Application of the framework on case studies

This article explores the implications of our proposed analytical framework on two case studies. The first one concerns energy efficiency in mobile networks, through the deployment of 5G in France. The second one centers on the question of the environmental impacts of *Machine Learning* (ML) models training. Both of these case studies explore current ICT deployment at the center of environmental controversies, in which the notion of rebound effect is mobilized against discourses promoting energy efficiency as a lever for decreasing, or at least containing environmental impacts of a growing sector.

The case studies have been chosen because they are key digital technologies and based on the familiarity and knowledge of specific situations by the researchers. One of the authors who has written the first case study has been researching rebound effects of ICT for years, and has studied the environmental implications of 5G leading to several reports on the topic. Another author who has written the second case study has been working on the environmental assessment of ML model training as part of their doctoral research.

The case studies are approached through the analytical framework described in the previous section. We base our analysis on scientific publications, actors public discourse as well as technical specifications of the studied sociotechnical systems.

4. First case study: energy efficiency of 5G

We consider the advent of 5G and its roll-out in the specific case of France. The *International Telecommunication Union* (ITU) defined performance requirements for this new generation of mobile networks back in 2017 [188], the technology

itself being specified and normalized by the standards organizations of the 3GPP. 5G is expected to not only drastically improve user experience of existing mobile networks applications (e.g., video streaming), but also to enable completely new use cases (e.g., real-time applications in the industrial and health sector, Internet of things, virtual reality, etc.).

The introduction of 5G in France sparked strong oppositions mainly due to concerns about its potential effects on health and, above all, on the environment. A moratorium was even supported by local elected officials and by a citizens' assembly initiated by the French president [15, 46, 125]. In Europe and more specifically in France, the environmental controversy about 5G focused primarily on the power consumption of mobile networks, their energy efficiency, and a possible "*rebound effect*" [32, 168]. Academic papers [42, 80, 201, 198, 3, 43] and as well as reports [6, 48, 85, 78, 8, 7, 180] also generally refer to "*rebound effect*" to describe the potential increase in mobile traffic induced by the 5G roll-out. Much of the literature has at least partly embraced its standard interpretation, i.e., describing the effect as the unintended or unexpected consequences [48, 78, 8] of energy efficiency improvements, driven by price effects [6, 42, 48, 85, 8] on consumer behavior [201, 8, 3]. Yet, some academic authors have challenged this view, arguing that the concept may not be suitable to describe this specific case. For instance, both Williams et al. [201] and Cano and March [43] noted that the increase in mobile traffic is "*the planned aim of the roll-out of 5G, not a surprising side-effect,*" and proposed to distinguish this situation from a "*rebound effect in the traditional sense*" using respectively the terms "*intended rebound effect*" and "*intended induced effect.*" Even though academic research has identified that energy efficiency, per-bit prices, user behavior, new applications, and other technical aspects such as bandwidth and latency, seem to all potentially play a role in traffic increase, the precise contribution of these dimensions and their mutual dependencies still need to be clarified. We argue that focusing on the actors behind the introduction of 5G and energy efficiency measures, on their motivations, and on how the aforementioned dimensions interact with their strategies, may shed new light on the subject.

4.1. Technical features of 5G mobile networks

5G improves mobile networks performance compared to 4G in several aspects. It provides larger bandwidth thanks to millimeter waves, has better spectral efficiency in part due to the introduction of massive MIMO, reduces latency, improves transmission reliability, and allows higher connection density. It improves energy efficiency when the network is loaded as a consequence of greater spectral efficiency [188]. It also allows deeper and more effective sleep modes by limiting control signals, thus improving energy efficiency when the network is in unloaded conditions, but *Mobile Network Operators* (MNOs) are not forced to implement them.

As some of these features may be exclusive, three main usage profiles have been targeted: eMBB (Enhanced Mobile BroadBand) focuses high data rates allowed by large bandwidth and high spectral efficiency, URLLC (Ultra-Reliable and Low-Latency Communications) exploits low latency and ultra reliable connections for real-time applications, and mMTC (Massive Machine Type Communications) relies on high connection density and energy efficiency. Data streams of different natures can also be mixed with the introduction of virtualization.

4.2. Motivations for 5G introduction and energy efficiency

In this section we present the main motivations of the major actors promoting 5G in France, i.e., the ICT sector including MNOs, and the regulatory institutions.

Accommodate growing traffic demand. In 2020, representatives from both MNOs and the public powers alerted about a possible saturation of 4G mobile networks in the near future in France due to growing traffic [57, 64]. They announced that delaying 5G would imply either a degraded quality for consumers, or the installation of far more 4G antennas than would be required with 5G, not to mention that France would fall behind other countries, although this position was not shared by all the MNOs [33]. Therefore, 5G promised to dampen the growth of networks electricity consumption in case of large increases of traffic [184, 8], though in practice it had no observable effect on this trend in France [9].

The hypothesis of exogenous traffic growth, existing independently of technological improvements, has been disputed in the literature [79, 70, 201, 80, 200, 3, 43]. Industrial actors themselves expect 5G will increase the mobile traffic [89, 178, 91, 60, 61, 179, 62]. A long-term exponential growth of traffic, as assumed in the aforementioned studies, is actually very unlikely to happen if we limit networks to 4G [79, 201, 80]. This is confirmed by the observation of the total volume of mobile data and per SIM card, which were both growing linearly at the time 5G was launched in France [47]. Taking into account the traffic induced by 5G can reverse the conclusion about its mitigating effect on energy consumption [79, 80, 97]. To summarize, as “*current network development is not oriented to serve a priori demand, but [...] is the responsible for stimulating that demand*” [43], it is “*likely that 5G will itself be the cause of at least some of the traffic growth it is being promoted as a necessary solution to*” [201].

Develop new applications. Applications envisioned for 5G have been grouped into three main usage scenarios: eMBB (e.g., 4K or 3D video streaming, alternative to fixed fiber-optic Internet access, cloud gaming and virtual reality when combined with low-latency), URLLC (e.g. self-driving cars, Industry 4.0, telesurgery), and mMTC (e.g., Internet of Things, smart cities). There are also synergies between the development of 5G and edge computing and artificial intelligence. Some of these applications can be achieved using existing wireless technologies (e.g. LoRa, Sigfox, Wi-Fi), but 5G can improve their performance and allows the deployment of different use cases within the same network [22]. These applications are often presented as essential by the ICT industry, following a rhetoric of self-justification transforming technical options into necessities [200], even though they do not necessarily correspond to a demand from the consumers, particularly in Europe and France [93, 94, 200]. In 2019, the GSM Association concluded from its consumer survey that “*there [was] still work to do to convince consumers of the benefits of the move to 5G*” [93].

Economic motivations. Digital technologies, and 5G and connectivity in particular, are regarded as a source of competitiveness, innovation, and value creation [125,

66, 199], hence they are a pillar of European and French public policies for restoring economic growth (e.g. the EU Lisbon Strategy in 2000 and France Relance in 2020).

Traffic growth is a source of profits especially for the ICT sector itself [198, 199], but over the last 20 years mobile networks operators (MNOs), particularly European and French, struggled to capture the value created by the digital economy [89, 90, 94, 61, 10]. They show the least revenue growth among the digital ecosystem, decreasing market capitalizations for most of them, the largest investment intensities [10], and the largest tax contributions in France [71]. They also face ever increasing data traffic [10], leading to what is often conceptualized as a “*revenue gap*” [133, 136, 152, 179].

In this context, 5G is seen as an opportunity to “*reverse revenue stagnation*” [61] and generate “*new streams of revenue*” [199] thanks to the “*monetisation*” of its performance and use cases, even though consumers’ willingness to pay premium prices for 5G remains unknown and a source of concerns from the sector [49, 89, 60, 91, 93, 92, 94, 61, 179, 199]. Another threat for MNOs is the networks electricity consumption which already represents a significant part of their OPEX [136, 90]. The risk of skyrocketing electricity bills was identified very early on by the industry [135, 90]. In 2019 the GSM Association made “*energy cost optimization [a] priority*” and enjoined MNOs to “*start planning their 5G-era energy optimization strategies now*” since “*energy costs can make a big dent in operator profit margins*” [90]. Energy efficiency is primarily seen as a way to minimize costs “*without degrading performance*” [135], and, as a result, has no minimum performance requirement in the 5G specifications [188]. Technical decisions regarding energy consumption (e.g. sleep modes) are thus left to the discretion of the MNOs [135].

4.3. Absence of traffic growth poses a risk to MNOs

Is traffic growth an unintended and undesirable side-effect of energy efficiency improvements brought by 5G in an effort of reducing networks energy consumption, as the term “*rebound effect*” suggests?

In France, regulations on minimal coverage and performance imposed to MNOs for 5G seem to acknowledge that 5G will significantly accelerate traffic growth [180]. Our analysis of actors' motivations also shows that the industry not only expect traffic to grow due to 5G, but even count on this growth to generate profits, and to escape from revenue stagnation in the case of MNOs. Two threats have been clearly identified by the sector: the explosion of operational costs and a lack of consumer adoption. Hence, traffic growth is not only intended by the actors as a means to achieve their economic goals, but its absence represents a serious risk to MNOs. Such growth is related to new uses technically enabled by data rates, connection density, and latency of 5G, rather than to energy efficiency. Nonetheless, energy efficiency is an essential enabler of economic viability, and an integral part of MNOs' development strategies. This explains why neither 5G specifications, nor the regulator in the case of France, have set constraints or quantitative requirements regarding 5G energy consumption, as opposed to the other performance criteria. Improving energy efficiency is thus considered by the sector as a secondary topic, mostly related to MNOs' profitability and motivated by economic sustainability, not environmental sustainability. MNOs can optimize energy consumption as long as they do not hinder network performance and the development of 5G use cases.

To conclude, even though 5G can improve energy efficiency of mobile networks, it should increase *typical* (in the sense proposed by Deng and Williams [54]) energy consumption due to improved *functionality* and new applications which are the *raison d'être* of this technology.

5. Second case study: energy efficiency in AI training

Our second case study revolves around the question of energy efficiency in AI models training. We will focus on *Deep Learning* (DL) models as this specific class of ML, and more generally AI, form the current dominant paradigm of AI research. The carbon footprint associated with the energy consumption used to train AI models has become a matter of scientific and even public

concern [53]. The seminal paper by Strubell et al. [177] sparked important discussions on the carbon footprint of model training and researchers stated the need for a “*Green AI*” [167], soon structured as an entire research field [186, 192]. AI causes large environmental impacts beyond its energy consumption at training, with other types of impacts such as water consumption [120] or metallic resource depletion [131, 21], and impacts during the whole life-cycle of the models including the corpus constitution, and the inference phases [121, 202]. Our case study will focus solely on the question of model training as it is the most documented part of the process.

Studies such as the ones by Strubell et al. [177] or Luccioni et al. [124] have documented the high carbon footprint of training single *Natural Language Processing* (NLP) models. Major AI companies have claimed that algorithm optimization, frequent hardware updates and impact shifting could mitigate [203] or even reduce the carbon footprint of AI training [142]. Academics have also pointed a trend of exponential growth of compute demand for AI models training [170, 183], sparking questions on rebound effect in AI training [123, 132].

5.1. ML training efficiency definitions depend both on software and hardware characteristics of the models

A specific trained DL model can be described by its *architecture*, trained *weights* and *performance* on a particular set of benchmarks. The model architecture sets how many *parameters* are in the model, and how they are inter-connected. The specific values assigned to each parameter, called weights of the models, define models outputs based on its inputs. Model performance is assessed using benchmarks defining sets of inputs and associated expected correct outputs.

The specific values for the models weights are obtained after performing a *training process*, i.e., the process used to turn random values initially set to each weights into the final trained weights. This process depends on the *training dataset* and requires *compute*. The used *training dataset* is very influential as ML is a statistical process that requires (a lot) of data that serve as examples of what the model should learn. Compute demand notably depends on the number

of parameters and on the dataset size.

Model performance, number of parameters, compute demand, and dataset size are all intertwined. Too few parameters or compute compared with dataset size might lead to incomplete assimilation of the dataset information. Too many parameters or compute compared with the dataset size might lead to model overfitting, reducing generalization capabilities and model performance on other datasets.

We have thus far focused on presenting DL models as a form of software, with different technical properties and a notion of performance. Performing the training process also requires hardware to run the compute. The training processes use a certain quantity of resources like time, energy or number of graphics cards. Realizing a fixed amount of compute requires different amounts of resources on different types of hardware. This first account of the links between the software and hardware of ML models highlights different aspects that can be understood as forms of efficiency based on the amount of resources used in the training process to achieve a certain level of performance.

Specialized infrastructure like datacenters are used for running large training processes, as they offer access to more powerful machines, and large parallelization capabilities. Datacenter operation requires supplementary resources, such as specialized cooling, in addition to the ones required to operate the individual machines. This supplementary resource consumption requirement can serve as a basis to define different forms of datacenter efficiency like *Power Usage Efficiency* (PUE) [11] or *Water Usage Efficiency* (WUE) [120].

Running training processes on datacenters allows for delocalising operations, as the machines do not anymore need to be in the same room as the people initiating the training processes. This opens a reflection on the environmental impacts of electricity mixes in different geographic localisation and for the definition of another form of efficiency through the notion of carbon intensity of the used electricity [171].

AI actors frequently discuss energy efficiency notions. This is however not necessarily their principal concern. We now focus on what are their objectives,

what tactics they put in place to attain them, and what roles do the different technical characteristics of DL models training play in these tactics.

5.2. Actors intend on increasing model performance through scaling

In this section we focus on the motivation of AI research communities. It is to note that AI communities are very intertwined with industry actors [2]. This implies that research subjects, practices and orientations are, to a certain extent, aligned with industrial interests. Most large language models are industrial projects, but are also presented as academic outputs, with at least preprints on the arXiv platform presenting the models.

We follow the analysis of Varoquaux et al. [190] that ML communities follow a 'bigger is better' paradigm. This paradigm is grounded in the observation or belief that scaling ML models leads to increased performance. Wagstaff [196] and Birhane et al. [27] show how the ML community highly values algorithm/model development over other contributions. ML models are primarily assessed on their performance on specific benchmarks [147, 63]. ML practitioners thus aim at producing new models maximising performance on these benchmarks.

Model scaling does not systematically lead to increased performance [190]. Still, empirical trends relating model size, training dataset size, or compute and performance have been established in the form of *scaling laws* [103, 98, 108]. These scaling laws have been widely discussed and have had a great impact on ML research, with thousands of citations according to Google Scholar. Analyses even suggest that increases in compute requirements are the primary source for performance improvement in the last decade [107]. A huge research focus is thus put on how to scale ML models. Scaling models requires increasing both training dataset sizes and model size.

Scaling training datasets. The amount of quality (labeled) data for any specific task is limited. An approach to increasing training datasets size is therefore to train more generalist models. This approach undergirds current large language models, which are all-purpose textual models. It allows to use all types of data

in a specific modality to train models. Large language models are for instance trained on vast quantities of text scrapped from the internet. The size of training datasets for the largest models are however approaching total availability of human generated textual data [193]. Researchers thus explore ways in which data limitations could be overcome in the future, for instance through multi-modal models (using both textual and image data in their training process) or through the generation of synthetic data [169].

Scaling model sizes. The other aspect that requires scaling is model size. The main challenge to model scaling, is to be able to perform the training process. Different limitations exist that might impede on that goal, such as the time to perform the required compute, or the cost or energy consumption of the process. Algorithmic progress allows to achieve a fixed level of performance using less compute, and also allows for more parallelization of compute, as with the shift from recurrent models such as *Long Short-Term Memory* (LSTM) networks to the transformer architecture which offers much better parallelization opportunities [191]. Still, as the goal is better performance, and not the same performance using less resources, compute requirements are to be increased, as is empirically observed [170, 183].

Handling scaling compute requirements. Larger financial and time investments are a way to face the increasing compute requirements. For instance a training time of five to six days using two GPUs was considered the maximum tolerable amount of time for training the landmark AlexNet model in 2012 [116]. These requirements are dwarfed by current practices, with the Llama 3.1 model released in 2024 which was trained for more than 50 days using more than 24,000 graphics cards [138, 141].

Mobilizing newer hardware, which can perform more operations per second and have more memory and data transfer capabilities, can serve to scale training processes. This hardware indeed allows for more parallelization through increased data throughput and further prevents too stark increases in training times from increased compute demand as it is also faster. This hardware is also incidentally

more energy efficient as it can perform more operations per consumed kWh. This form of energy efficiency is however secondary to the possibilities of overcoming different bottlenecks toward bigger models training in the reasons for hardware renewal.

Still, larger investments cannot do everything by themselves. Tolerable training duration can only be increased to a certain extent. Training times of more than a few month might be prohibitive in a very competitive and quickly evolving environment. Used facilities can be limited in the quantity of available hardware, in energy provisioning or even in their heat dissipation capacities. In that context increasing data center efficiency can be used to “*overcome power constraints*” and to prevent too large increases in operational costs, as advertised by NVIDIA [139].

Managing environmental critique. Finally, the question of the environmental impacts of model training is also a matter of public scrutiny. In reaction to the critique of the large environmental impacts of the field, a small subset of AI research focuses on trying to develop a “*Green AI*” [167]. Their work however do not seem to be able to counteract the trend in scaling models, which is at the heart of the growth in model training impacts [132]. AI companies may fear facing reputational damage if they do not address environmental critique, as illustrated by internal communication at Amazon leaked by the Guardian [14]. Big techs communication on their efforts to increase energy efficiency, while their total footprint increases, can thus be read as a way to plead good faith and mitigate reputational risk. Another aspect to the communication tactic is to insist on the potential role AI could play in climate change mitigation⁸, even if these gains are yet to be proven on a large scale [65, 121, 112].

⁸This aspect is very present in the environmental reports of the big tech companies. See for instance the Google report from 2025 [81].

5.3. Energy efficiency plays an enabling role for scaling models

ML models training has a growing resource demand. Using the concept of rebound effect suggests that it is an unintended and undesirable side-effect of increased energy efficiency.

As outlined in our analysis of actors motivations, AI research and development is driven by an objective of producing models with increased performances on different sets of benchmarks. The field is dominated by a 'bigger is better paradigm', meaning that an important part of actors tactics aims at allowing for larger training processes.

Our analysis first shows how energy efficiency is meshed in a network of evolving functionalities, with for instance better benchmark performance or more generic models. New models use more data, different model architectures with increased parallelization capabilities, more efficient hardware, and more hardware in general. This implies that new training processes do not correspond to the exact same activity as previous ones.

Second, we highlighted how energy efficiency appears in a context of scaling. Bigger jobs can be made more efficient with opportunities for economies of scale. Examples of this are the average reduction of PUE when moving toward bigger datacenters [128] or the increased compute efficiency of newer hardware that has increased compute capabilities. Using the framing of Deng and Williams [54], we can say that while new hardware or hyperscale datacenter are more energy efficient in terms of *functionality* (i.e, requires less energy for a fixed compute demand), they are not necessarily more efficient in terms of *typical use* (as actors aim at increasing compute demand). The fact that the total energy consumption of graphics cards used for ML models training has stayed mostly flat over the last decade [132] can be interpreted as a sign that the new graphics cards have stayed at approximately constant energy efficiency levels in terms of typical use. In such a context of scaling, energy, time or other cost optimization, as long as they do not hinder on performance which is the main objective, are thus more likely to be re-used for model scaling than for reducing energy consumption.

Third, energy efficiency is one of the factors allowing scaling. Continued scaling of training processes requires overcoming different limits. Diverse approaches are mobilized by actors including increased investments and diverse forms of technical innovations. Increased energy efficiency is one of the different forms of technical innovations required to overcome limitations in power provisioning for datacenters, and to contain the increases in costs related to energy expenditures. Increased energy efficiency can also be mobilized by actors to manage environmental critique and thus continue scaling while mitigating reputational risk.

We can thus conclude that reducing energy consumption of the training processes through energy efficiency is not the primary aim of actors, and is secondary to creating bigger models with increased benchmark performance. The growth of ML models, as intended by AI companies, depends on the various forms of efficiency that they promote. However, in this context, efficiency primarily acts as an enabler of growth instead of a way to mitigate impacts. Framing these observations as a rebound effects would imply that the growth is unexpected, whereas efficiency improvements seem to aim mostly at enabling larger models.

6. Discussion

In this article we discuss the notion of rebound effect and propose an alternative framework to assess the role of energy efficiency in cases where this notion is frequently applied in ICT. Our framework centers on accounting for the sociotechnical context around energy efficiency in a specific technology. This is realized through contextualizing energy efficiency in relation to other technical characteristics of the studied technology, and by studying the roles and tactics of actors in the studied technological developments.

6.1. Our framing better explains environmental dynamics than rebound effect in our case studies

We applied our framework on two case studies regarding controversies around energy consumption and its evolution in the deployment of 5G in France and in

ML models training. In these two cases, increasing energy efficiency over time is often portrayed as helping towards a reduction in energy consumption but with risks of rebound effects that could negate the gains.

We showed in both case studies that increased demand (traffic growth for 5G and larger training processes for ML) are not an unintended and undesirable side-effect of energy efficiency improvements brought by technological changes (deployment of 5G over 4G, and software, hardware and infrastructure optimizations for ML) in an effort of energy consumption reduction or mitigation. This is contrary to what is suggested by the use of the term rebound effect in analysing these same case studies.

The analysis of the 5G case shows how traffic growth is a desirable scenario for MNOs, as its absence would pose a risk to their economic sustainability. This contradicts the usual rebound effect framing where traffic growth is framed as a risk of increasing energy efficiency of the networks, encouraging more intense uses. The case of ML training also shows how energy efficiency is one of the levers that actors use in order to allow for scaling training processes.

Our analyses show how energy consumption reduction, and even energy efficiency to a minor extent, is not a primary concern of actors in both case studies. Actors would probably be glad if energy consumption stagnates or even decreases, but their actions are not primarily aimed at achieving this effect. Increased energy efficiency sometimes happens as a side effect of actions leveraging another technical feature. In our case studies, this is observed on some levers, such as increased spectral efficiency of newer networks, or training processes occurring on larger scale datacenters. In these instances, energy efficiency increases as a side effect of changes which were not primarily motivated by a goal of reducing energy consumption.

The notion of rebound effect often centers attention on user behaviors. In that framing, rebound effect occurs as the aggregation of users individual choices. Our framework focuses on the pivotal role of actors designing and deploying technological changes. By focusing on these actors, we highlight their influence in shaping both energy efficiency, and the potentialities it has

in interaction with the specific deployment context and interactions with other technological aspects. As with the work of Galvin [73], this shows that there also is a major collective responsibility of technology providers in environmental (un)sustainability.

The notion of rebound effect, as it is frequently applied in ICT, thus presents a simplistic and inadequate vision of the dynamics at play in our case studies. Our approach allows to bring along complexity and thus better understand the mechanisms driving the observed trends in energy consumption.

Both of our case studies present actors with an intention or even a necessity for activity growth. Energy efficiency is leveraged, among other technical changes, to achieve and continue the desired growth. These situations are different from the rebound effect framing in that they do not present an aim of impact reduction. Also, the necessity of energy efficiency for achieving growth means that energy efficiency does not necessarily imply an initial reduction or mitigation of impacts. We propose to denote of our case studies as situations of *intended enablement*. This notion could be applied to any other situation with an intention for growth of activity, and where increased efficiency is leveraged to sustain that growth.

6.2. *Intended enablement are frequent in ICT*

ICT development and deployment often present multiple similarities with the case studies we presented in this article. Digital technologies evolves rapidly, with important variations in functionality and an industry in strong economic growth. Our framework can be applied to these other cases, helping to better understand the place and role of energy efficiency in these technological developments.

We have focused our analyses on the role of energy efficiency in a specific sociotechnical context. We showed how it is leveraged by actors in order to achieve growth of activities in our case studies. Similar dynamics can however appear around other resources, as with the case of run time which also appeared in the AI case.

Our critique of the rebound effect framing focused on cases of optimizations

of ICT infrastructures and direct rebound effects. We could also certainly obtain similar conclusions studying cases where ICT serves to optimize systems in other sectors, and where the motivations for the optimizations are probably very similar: with goals of increased activity more than environmental impact reduction.

6.3. Implications of using our framework for other case studies

Identifying intended enablements during design processes. Our framework is more meant as a tool for critical understanding and assessment of digitalization processes rather than a design tool. Still, our approach could be adapted for a design process. This would for instance correspond to a process that starts by identifying what are the motivations and deployment context behind an envisioned digitalization process. Next steps could discuss what could potential risks be and how to handle them. This could ultimately be used to devise actions. From this basis, intended enablements could be exhibited, and serve for the creation of system-design models such as causal loop diagrams [59].

Accounting for intended enablements in environmental assessments. We have shown how rebound effect is inadequate for describing the dynamics at play in our case studies. Both cases can be described as situations where energy efficiency serves intended enablements. As we consider that the observed intensification of activity forms a direct consequence of digitalization, we call for such effects to be systematically accounted for in assessments. This also calls into question the traditional separation between direct and indirect effects of digitalization.

Typical methodologies for assessing the so called net environmental impacts of digital services use a comparative LCA approach. This approach requires defining a *baseline scenario*, reflecting the current practices and state of affairs, and one or more *deployment scenarios* using the digital service. An LCA is performed for each scenario, using the same functional unit and to the best extent, the same scope. Results are then compared between the deployment and baseline scenarios, allowing to produce assessments of the net environmental

impact of a digital tool or service (including both the direct life-cycle impacts, and potential substitutions for instance).

When assessing environmental impacts of new digital services aimed at increasing activity, however, the baseline scenario should reflect current service level while the deployment scenario should consider increased service in order to reflect the intended enablement [51]. Such a differentiated service level, means that baseline scenarios and deployment scenarios would not be assessed with the same functional unit. The deployment scenarios indeed allow to account for increased activity, thus fulfilling a different function than in the baseline.

This approach broadly corresponds to the proposal for dynamic LCAs at the *typical product* level proposed by Deng and Williams [54]. This would not however affect choices for scope of the assessments that should be as close as possible in the baseline scenarios and in the deployment scenarios. The methodological framework proposed in this paper helps in identifying typical product uses.

Policy implications for our case studies. Our case studies show instances where increased activity is the desirable scenarios for key stakeholders. Our analysis shows that increased energy efficiency is essential for the studied scenarios to be beneficial. In the 5G case, network operators risk economic unsustainability without efficiency gains; in the ML case, efficiency is needed to overcome power limits and enable further scaling. These cases differ notably from the typical rebound-effect narrative and must be addressed properly to mitigate environmental impacts.

In our case studies, environmental impact mitigation through activity reduction is directly at odds with the key stakeholders goal (increased activity). Addressing environmental impacts with eco-design is consistent with the prioritization of activity over reduced environmental impact, as in the ML case. A sufficiency mindset would instead lead to question the need for digital activity growth, as well as digitalization in general, owing to the associated adverse environmental and social impacts.

Implications for green IT activities in intended enablement situations. In situations of intended enablements, some actors actively promote increased activity, and leverage energy efficiency to that end. In practice, these actors may use energy efficiency gains to increase activity in spite of designers' intent. While work on energy efficiency can be environmentally beneficial even in intended enablement contexts, we would like to encourage stakeholder awareness of the sociotechnical context and their contribution to enablement goals.

7. Conclusion

In this article, we challenge the notion of rebound effect which is insufficient to understanding and address the environmental impacts of digitalization. We propose a methodological framework to describe the sociotechnical context around energy efficiency in ICT and applied it to two case studies evidencing that stakeholders express an intention or even a need for activity growth. Energy efficiency is one of the key levers to achieve growth. We show that the notion of rebound effect is therefore inadequate to describe the dynamics at play in our case studies. Indeed, energy efficiency is not used (principally) to reduce impact, but to allow for the creation of new uses. We think that similar conclusions could be obtained on numerous other forms of digitalization by using our methodological framework. Our results suggest not only to depart from the mechanistic interpretation rebound effects, following Galvin [74] and Ruzzenenti and Wagner [150], but also to interpret the rhetoric of efficiency in environmental debates as a way to maintain the status quo and protect interest, in line with the work of Shove [172] and Ruzzenenti and Wagner [150].

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