Towards Energy-Efficient Large-Scale Artificial Intelligence for Sustainable Data Centers

Dusan Dokic[1], Hannah Stein[1], Sabine Janzen[1], Wolfgang Maaß[1]

Abstract: The growing interest in AI services has led to a higher demand for computing power to train and execute complex AI models, causing a surge in power consumption in data centers. Together with rising costs for electricity, gas, petroleum, and coal, and the national target for climate neutrality of data centers by 2027, the ability to operate data centers economically is threatened in Germany. To address these issues, a pressing need to improve the sustainability of data centers and that of artificial intelligence. This paper proposes a roadmap to develop sustainable and resource-efficient data centers and AI systems. The roadmap includes four key building blocks: sustainable data centers, AI algorithms, AI sustainability framework, and economic efficiency analysis. Each building block poses pivotal research questions grounded in contemporary literature to guide the pursuit of environmental sustainability in data centers and AI.

Keywords: Data Centers; Sustainable AI; Energy-Efficient AI Algorithms

1 Introduction

The electricity demand of German data centers has increased by 30 % since 2016 and has more than doubled in the past ten years - from 5.8 billion in 2010 to 16 billion kWh in 2020 [St20, Hi22b], as three quarters of all companies in Germany use data centers for operating and developing business-critical IT applications [Bu21, Hi22b]. The training of artificial intelligence (AI) models can be identified as one of the main drivers of this growth as training large AI models can emit the equivalent of five SUV lifetimes (284 tons of CO_2.) [Ne22].

For this reason, the energy consumption of AI models must be addressed as they require more computing power as their complexity increases[SGM19]. Solutions to increase the efficiency of the models are necessary to manage the demand for computing power and minimize the resulting environmental impact. In order to achieve this, tools for measuring and monitoring environmental impact must be used in conjunction with new technologies that surpass the limitations of previous hardware [Th22, Wa20]. Currently, companies developing AI-based services for innovative business models, have no tools to help them to manage the implementation including training and operation of the AI models via energy and sustainability monitoring [Bo20].

[1] Deutsches Forschungszentrum für Künstliche Intelligenz GmbH, Smart Service Engineering, Stuhlsatzenhausweg 3, 66123 Saarbrücken, Deutschland, {dusan.dokic;hannah.stein;sabine.janzen;wolfgang.maass}@dfki.de

This work addresses these shortcomings by developing a roadmap for improving the sustainability of data center and AI-systems. In the roadmap we outline the necessary research that has yet to be undertaken, such as the development of a concept for the sustainable, resource-efficient design of data centers and AI systems as well as a framework that can be used to measure the sustainability of AI systems so that practitioners can make more informed decisions on the application of AI models in favor of a more sustainable solution, environmentally and ecologically.
The paper is structured as follows: Building on the state of the art on the sustainability of data centers and AI, we propose a research road map consisting of four building blocks. We suggest possible pathways for further research including possible research questions. We conclude the paper by summarizing and giving an outlook on our future work.

2 State of the Art

2.1 Sustainability of Data Centers

Numerous factors influence the sustainability of data centers. In addition to the energy efficiency of the hardware installed in the servers (e.g. GPU, CPU), cooling and energy management systems also play a major role [LDM20]. [FT12] provide an overview of the main components responsible for the majority of energy consumption in data centers. In addition, the share of renewable energy in the total consumption and metrics to measure sustainability represent major factors [Wh14]. [LMG18] propose a model for assessing the environmental impact and operational efficiency of data centers. Research in sustainable data centers has already produced numerous metrics to measure data center energy efficiency in an attempt to measure and manage energy consumption [Wh14] such as the power usage effectiveness value [Th07] or the green energy coefficient [Th14]. However, these metrics are criticized for their limited view as they only include the operating phase of the data centers [Wh14]. For this reason, life-cycle-based approaches are increasingly adopted in an attempt to consider data center sustainability across all phases [Gu22, WAS15a, WAS15b]. Despite current efforts to make data centers more sustainable, existing hardware (CPU, GPU, TPU) is reaching its limits in terms of efficient training of ever larger AI models [Th22]. Because of this, research is investigating new hardware technology such as neuromorphic chips; these are designed to mimic the structure and functioning of the human brain and promise efficiency gains of up to 50 % for training and 80 % in inference for certain AI models [Su20]. Despite the promising positive impacts of neuromorphic technologies, the research is still at a beginning stage and more research into the topic is needed [Sc22].

2.2 Sustainability of AI

According to [vW21], Sustainable AI is ‘a movement to promote change throughout the life-cycle of AI products towards greater ecological integrity and social justice’ and is divided into ‘AI for sustainability’ and ‘sustainability of AI’. Academia currently focuses on the aspect of ‘AI for sustainability’ and explore how the use of AI can mitigate the effects of climate change [SM22, OE22]. While concentrating on the positive effects AI applications can have on the environment, the resource consumption required to develop and use AI are neglected. ‘Sustainability of AI’ addresses this issue and discusses principles for developing sustainable AI [MI22]. Building on this, [Li22] offered a preliminary approach for implementing an AI life-cycle assessment (LCA) in practice. Their work is foundational in defining the system boundary in the context of AI LCA, contributing significantly to our understanding of AI’s environmental impacts. In a recent paper, [RSC23] review the current body of knowledge and examine 98 paper relating to Sustainable AI or „Green AI“ and conclude that there is little work considering the environmental impact of AI as a whole, apart from energy use. They highlight the lack of tools to implement Sustainable AI and urge researchers to use the current body of knowledge to develop such tools for practitioners.

2.3 A Framework for Measuring the sustainability of AI

The discussed trade-off between ’AI for Sustainability’ and ’Sustainability of AI’ poses forces decision makers to carefully consider all positive and negative environmental impact before introducing AI applications [ZGF23]. However, in order to do this, they need information about the consumption and environmental impact of the AI application. In this regard, some scientific works can already be found that aim to measure the power consumption of different algorithms or AI models [He20, Me23, Mi21] and methods to improve energy efficiency during training by applying so-called green coding principles [Gr22] or optimized ’work flows’ [LCC22]. In addition, work such as that of [Ka22] shows that frameworks for capturing the environmental impact of AI are needed and must capture multiple levels and factors than just the operational phase and power consumption. This finding, combined with the fact that current research in this area primarily lacks tools to implement current research [RSC23], leads us to conclude that a framework is needed that captures the environmental impact of AI systems in their entirety and provides decision support for the sustainable use of AI applications.

2.4 Economic Efficiency Analysis of Sustainable Data Center

Artificial intelligence is already embedded in the business models of many companies and is also already being used to make them more sustainable [To20]. In their comprehensive review on AI and sustainable business models, [Di20] found that it is mostly used to improve sustainability aspects but also aspects of ethics and finance. However, in the context of data centers, it is not only a matter of integrating business models with the help of AI, but also of taking into account the influence of AI as a product, which is directly related to the costs of a data center [Na19] , and combining these with sustainability aspects of other business model components such as the building location and technical equipment [LDM20]. To this end, standards and norms already exist for the operation of conventional data centers from which business models can be derived [DI19]. But there are only a few studies that analyze and evaluate the efficiency of "green data centers"[Pe16, Sh17] and conventional data center models only consider proven hardware such as CPU and GPU. An economic analysis of new hardware such as NPUs [Sc22] for use in the data center, is currently lacking. Even tough, the resulting efficiency gains [Su20] could strongly influence the business model, especially of AI-focused data centers, and improve previously unprofitable lines of business [Da09].

3 A Research Roadmap towards Sustainable Data Centers and AI Systems

Building on related work and current shortcomings, we propose a research roadmap for future work in the development of sustainable AI and data centers. We propose four building blocks, namely the conceptualization of sustainable data centers, frameworks for measuring the sustainability of AI, development of sustainable AI algorithms as well as economic efficiency analyses. We summarize the research roadmap in table 1, including short descriptions of the building blocks and potential research questions.

3.1 Conceptualizing Sustainable Data Centers

To conceptualize sustainable data centers, hardware and software-related aspects need to be considered. We argue that sustainable data centers should appraise the utilization of neuromorphic chip technologies in the form of Neuromorphic Processing Units (NPU) as conservative estimates expect NPUs to reduce data center energy consumption up to 47.5 % [Hi22a]. In terms of hardware, hybrid architecture should be exploited, allowing traditional GPU/CPU/TPU-based data centers to be combined with NPUs. Additionally, it needs to be investigated for which use cases classic GPUs can be completely replaced by NPUs, so that a concept for a purely AI focused data center for an energy-efficient training of large, resource-intensive AI models such as Natural Language Processing (NLP) and Visual Computing (VC) can be designed. This leads to the following research questions: RQ1: 'How can NPUs be integrated into existing data center architectures to enable a hybrid concept?' and RQ2: 'Under what circumstances does replacing existing hardware in data centers like GPUs with NPUs have a positive impact on the environment?'.

3.2 Sustainable AI Algorithms

The 'sustainability of AI' is becoming increasingly important due to larger and larger AI models with billions of parameters that need to be trained and adapted and consume more and more resources [SGM19]. Neuromorphic chip architectures have potential to reduce this consumption, but the algorithms for these architectures are not yet as mature as for traditional chip architectures and current algorithms still need to be adapted to the new architecture. Therefore, a re-implementation of traditional AI algorithms on neuromorphic chip architectures is required, taking into account green-coding principles [Gr22], in order to achieve improved energy efficiency and increased sustainability of the developed algorithms. The research questions that need to be answered are therefore RQ3: 'How can traditional AI algorithms be adapted to neuromorphic hardware?' and RQ4: 'Are AI algorithms implemented on neuromorphic hardware more sustainable or energy efficient in training and inference than traditional AI algorithms?'.

3.3 The AI Sustainability Framework

Global challenges such as climate change can only be addressed if companies become sustainable and environmentally friendly [vZvT21]. Based on the 17 SDGs of the United Nations, it was found that AI can have a positive impact on a large part of the SDGs [Sc23]. However, the 'lack of understanding of the use of AI in the primary and supporting functions of organizations' [SM22] and the lack of measurement capabilities to verify the environmental sustainability of AI systems [OE22] currently prevent the exploitation of the positive impact AI can have on the environment. Since the data processing of AI systems requires energy, but their application can result in energy savings, this derives an optimization problem via an AI sustainability framework model. The application of the AI-SF requires measurement data collected at different levels: the technical level, the application level and the systemic level [Ka22]. The technical level primarily considers the computing power that must be expended to develop an AI model and apply it. Here, the individual life cycles of model development such as data collection, training, inference and adaptation are considered. In addition to the computing power, other factors need to be taken into account, such as building technology, sustainability of energy used [DI19], total costs of the hardware and software used and personnel deployment [DI17]. The application level considers the positive and negative impacts that result from the use of AI [Ka22]. In addition to direct effects, the use of AI also entails indirect effects, which have an impact on the environment at a systemic level [BM22].
To implement such a framework, it requires the design of models to measure the various aspects of sustainability of AI systems, such as emissions and energy and resource consumption [Ro21]. The measurement models must be able to be used generically for classical and innovative technical architectures and span the range of technology, application, and system. The integrated measurement model is iteratively designed using the framework model (AI-SF). From the AI-SF, an AI-based optimization model will be derived to make predictions about the sustainability of AI applications in AI data centers. This model will be tested and optimized on real data. On the decision-making level, the forecasts will be used to optimize AI applications with respect to their effects on the environment or rebound effects. Research questions will be RQ5: 'How can the overall environmental footprint of AI

applications be measured and optimized?'. These measurement models and the AI-SF will then be translated into software modules and a platform usable by end users in future work.

3.4 Economic Efficiency Analysis

The computational needs of AI systems are growing, leading to a quadrupling of data center power consumption by 2030 [An20]; raising sustainability concerns among policymakers. For example, the german government's coalition agreement stipulates that data centers must become carbon neutral by 2027, while the OECD is pushing to fill current gaps in measuring the environmental impact of AI, including addressing the aspect of computing power [OE22]. Still, efforts to increase energy efficiency in data centers have stagnated over the past decade, as further optimization would only allow marginal returns at high costs [Bi21]. Long-term environmental sustainability in data centers hinges on its integration into their business model, while considering economic factors. Utilizing energy-efficient neuromorphic chips for AI training can boost efficiency and profitability, also opening new business prospects for both newcomers and established entities. The resulting research questions that need to be answered are RQ6 'What economic aspects need to be considered when using neuromorphic hardware in data centers to make it profitable?', RQ7 'What risks to the business model of traditional data centers need to be considered when using neuromorphic hardware in data centers?', and RQ8 'What does an economically and environmentally sustainable business model of a data center based on neuromorphic hardware look like?'

4 Conclusion

The discourse on 'AI for sustainability' highlights the need for a balanced approach that focuses on the environmental benefits AI can bring and addresses the significant resource consumption involved in its development and application. To this end, future research is urged to work on the identified building blocks such as the AI sustainability framework, that optimizes energy savings from AI applications against the energy expenditure in AI data processing. In summary, achieving sustainable AI and data centers has many complex considerations and hurdles. Nevertheless, the potential rewards are equally significant, not only for the environment but also for the data center business model. This work aims to be a starting point for future research and offers a research roadmap, presenting key questions that must be addressed to achieve environmental sustainability of data centers and AI.

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Appendix

Building Block	Short description	Possible Research Questions
Sustainable Data Centers	Designing a concept for sustainable data centers based on neuromorphic hardware for a 'hybrid' and 'cloud' architecture	How can NPUs be integrated into existing data center architectures to enable a hybrid concept? Under what circumstances does replacing existing hardware in data centers like GPUs with NPUs have a positive impact on the environment?
Sustainable AI Algorithms	Re-implementation of traditional AI algorithms on neuromorphic chip architecture and evaluation of efficiency gains	How can traditional AI algorithms be adapted to neuromorphic hardware? Are AI algorithms implemented on neuromorphic hardware more sustainable or energy efficient in training and inference than traditional AI algorithms?
AI Sustainability Framework	Solving the optimization problem of positive environmental AI impact and the necessary resource consumption by measuring and quantifying the impact and costs on the technical, the application and the systemic level	How can the overall environmental footprint of AI applications be measured and optimized?
Economic Efficiency Analysis	Integrating environmental sustainability into economically sustainable business models to ensure	What economic aspects need to be considered when using neuromorphic hardware in data centers to make it profitable? What risks to the business model of traditional data centers need to be considered when using neuromorphic hardware in data centers? What does an economically and environmentally sustainable business model of a data center based on neuromorphic hardware look like?

Tab. 1: Building blocks of sustainable data centers and AI system and open research questions