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Environmental impact of AI and data centres: considerations involving low energy computing

Submitted by:

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The views expressed in this submission are those of the named authors alone and do not necessarily reflect the positions of their research groups, the University of Manchester, or the Tyndall Centre.

The authors would be willing to provide oral evidence, if requested.

This submission addresses two current inquiries (*Risks and opportunities to the sustainability of data centres in the UK* [1] and *Low energy computing* [2]) and draws on the Research Briefing *Data centres: planning policy, sustainability, and resilience* [3]. It highlights the importance of contextualising, benchmarking and reporting on the environmental impact of AI and computing, and the need for interdisciplinary collaboration between policymakers, industry and academia. It begins with context and framing, outlines the case for robust measurement and reporting, places low-energy computing investments within that framework, and concludes with reflections on cross-sector collaboration as a route to policy-relevant impact.

1. AI energy use: context, scale and opportunity

Digital systems, as well as workflows and algorithms running on these systems, have been key to economic growth and national security since the dawn of computing. Artificial Intelligence, and particularly its subset of large language models, is a recent addition to this landscape. Large language models (LLMs) are currently in daily use for individuals, businesses and governments. Unlike more specialised algorithms, LLMs require substantial data and computational resources to be trained. The increased availability and use of these models means that data centres must process large numbers of user requests. **This stage, called *inference*, can consume more energy overall than training the model in the first place** [4]. These two aspects underpin the concerns about the energy use of data centres.

It is important to note that AI and large language models (LLMs) are not synonymous, although they are often treated as such.

Much of the recent growth in AI use, and the associated increase in energy demand, has been driven by commercial LLMs. Because these models are designed for many different tasks, they can be less energy-efficient than systems built for a more specific purpose. **More specialised AI systems can often deliver comparable results at lower energy cost** (see e.g. [5] [6]). The energy needed to run AI models can also be reduced in different ways, although the effect on output quality and speed depends on the method, the task and the available computing resources (see e.g. [7]).

These gains in energy efficiency still depend on the limits of conventional computing hardware. Further progress may also come from **emerging hardware approaches and alternative computing paradigms**, including methods such as neuromorphic and reservoir computing, which aim to reduce energy use through new forms of hardware design. These approaches already show significant efficiency gains for specific, well-defined tasks, and could be well matched to specialised architectures. However, scaling them up for broader general-purpose use remains a significant research challenge [8] and will require sustained investment to be met. Investment in this area works best when both fundamental and applied research are funded together, even when they sit in different fields or under different research councils. The relationship runs in both directions: fundamental research has a consistent track record of generating technologies beyond their original purposes (for example, the world wide web, GPS and medical physics instruments). Conversely, research communities with large-scale computational problems are important drivers of hardware and algorithm R&D as they supply the use cases, benchmarks and performance requirements that provide concrete targets. **Supporting co-development of low-energy hardware paradigms alongside the scientific and industrial communities that would deploy and stress-test them is therefore likely to be more effective than funding either of them in isolation.**

The strategy to keep AI energy use under control while maintaining useful performance will require continued support for **research on energy-efficient AI algorithms, the hardware needed to run them, and the scientific questions that drive progress in both.** Progress in these areas often depends on long-term research programmes rather than short funding cycles, and breakthroughs can be built on a series of smaller advances. **Investment therefore needs to be stable and sustained, so promising research directions are not abandoned too early,** and so that successful approaches can be adopted widely.

Greater efficiency in algorithms and hardware may not automatically reduce overall energy consumption: lowering the cost of a resource historically drives greater use [9]. Realising the benefits of more efficient AI and hardware will therefore also require **training, awareness and conscious choices at every level.** Policymakers, business and individuals, will all need enough information to judge when simpler and more specialised algorithms with smaller energy budgets are the right tools for a task, and will need to be encouraged to make a **responsible and sufficient use of AI algorithms.**

2. Measurements, reporting and standards

The discussion above, and in the Research Briefing in [3], focuses mainly on the operational energy and water consumption of data centres that run AI systems. However, **their environmental impact extends beyond operation.** It also includes the impacts associated to the hardware itself, generated through manufacturing, transportation and eventual disposal. These are often referred to *embodied* impacts. **Wider effects also include biodiversity loss, land use change and generation of hazardous electronic waste.**

Measuring this full impact require established international standards, such as those used in life cycle assessment (LCA) tools (ISO 14040/14044 [10]) together with clear boundaries on what is and what is not included.

Conducting such a full life cycle assessment according to standards is costly and requires effort and transparency from both manufacturers and stakeholders [11] in a way that still protects growth and confidentiality. However, it is necessary.

Current estimates of AI energy consumption based on scaling and extrapolations are not reliable, partly because of a lack of clarity on their baselines and of lack of development of standards for the sector, with consequences impacting both forecasting and reputation [12]. Furthermore, while not all embodied impacts occur directly in the UK (e.g. for specialised AI computer chips produced in Taiwan), one can envisage production on UK soil of new sovereign technologies which would then count as part of the UK impact under standard greenhouse gas accounting frameworks and fall within the UK's climate commitments. In any case, both corporate reporting and [Science Based Target initiative](#) standards encourage the inclusion of these impacts.

Grounding policy and investments in measurements that are compliant with measurement standards is necessary, especially given the scale of resources that are being committed to AI infrastructure and growth.

Transparency is needed both in how AI systems are assessed, and how the wider environmental impacts of the supporting hardware and data centres are measured. This is where UK policy can close a gap and has an opportunity to lead. EU regulation mandates annual reporting from data centres that exceed a given power demand using a standard EU template that covers operational footprint indicators such as energy and water consumption, capacity utilisation, and waste heat. In the UK, such reporting for data centres is not as structured [13]. Neither UK nor EU reporting strictly include embodied impacts.

One possible next step could be to bring together policymakers, industry and academic experts in both life cycle assessment and computing, to develop reporting standards that cover both operational and embodied impacts. This could then be introduced on a phased or voluntary basis, starting with research- and government-funded computing investments, where the case for transparency is strongest and a mandate can be established through consultations with the funding agencies.

Monitoring and reporting of the environmental impacts of computing could also be extended to alternative computing paradigms as these technologies mature. This discussion should remain evidence-based, keeping in mind that these are nascent technologies and are expected to become more (environmental-)cost-effective as their development progresses, and showcase what is already known and why continued investment is worthwhile.

As AI becomes more embedded in everyday life and economic growth, the UK has an opportunity to act early. International policy discussions have used the framing of a “triple win”: for climate, energy security and economic competitiveness in this context [14]. **The UK is well-placed to build efficient and sustainable AI algorithms and infrastructure, supported by robust methods for measurement and reporting.** Clear reporting standards will be important for showcasing the benefit of more efficient algorithms, more sustainable data centre operations, and emerging hardware technologies.

3. The importance of working across disciplines and sectors

Reducing the energy and environmental footprint of AI is inherently a multidisciplinary problem. It requires physicists, material scientists and computer scientists to develop algorithms and hardware, environmental scientists to measure real-world impact, and social scientists and policy experts to understand patterns of demand and behaviour and to design governance frameworks.

In this respect, the academic and research community may be somewhat underutilised relative to their potential (partly because existing engagement mechanisms are not always designed to fit alongside active research programmes). Alongside their expertise in the underlying research, **academics and researchers can offer independent evaluation of evidence, scrutiny of assumptions, and long-term institutional knowledge.**

While well-established routes for academics and researchers into policy exist (e.g. evidence sessions, secondments, advisers, policy reports from learned societies), they could be complemented by continuous, structured **engagement of a larger part of the academic and research community who are already working on the questions in these two inquiries.** One example is [NetDRIVE](#), a UKRI-funded network that brings together researchers, engineers and infrastructure managers to work on the sustainability of digital research infrastructures. This shows that there is already broad interest within the academic community in this kind of interdisciplinary work. Stronger connections to policy processes and input to reviews of commercial AI deployment could be a meaningful next step to be proposed to members of these communities.

Appendix A: preliminary list of metrics for distributed data centres in international research infrastructures (provided by C. Doglioni)

Within the EU-funded (Horizon Europe) ENSURE project, gathering experts from Research Infrastructures in UK and Europe, C. Doglioni has contributed to compiling a preliminary list of metrics to be monitored for distributed research data centres in international research infrastructures (ESFRIs). This list will be iterated upon over the course of the project (2026-2029) accounting for current reporting recommendations and legislation, and these metrics will be collected in a database designed and deployed by the Rutherford Appleton Laboratory in Didcot. This figure has been shown at the NetDRIVE Community Meeting in April 2025, and it can be found below. In this context, “job-level metrics” pertain to algorithms that will be executed on the data centre.

KPI (Key Performance Indicators)	Metrics	Metadata on methods
based on ISO 30134 / EN 50600, JRC C-GC, EED, ESRI reporting PUE (Power Usage Effectiveness) <i>Ratio of total energy used to energy used by IT</i> Carbon footprint: <i>CO₂ emissions associated w/ energy usage</i> Carbon Usage Effectiveness (CUE): <i>Energy Carbon Intensity (CI) to Energy consumed</i> Water Usage Efficiency (WUE) <i>Ratio of water to energy used for IT</i> Resource utilisation efficiency <i>(IT equipment energy efficiency & use)</i> <i>Servers, storage etc. benchmark vs power at load</i> Cooling system efficiency <i>(e.g. Cooling Efficiency Ratio)</i> <i>ASHRAE based KPIs</i> Energy Reuse Factor (ERF) <i>Waste heat exported / consumed</i>	Job-level metrics (from plug-ins) Energy consumption [kWh] CPU time / wall time [s] for static measurements (e.g. TDE) Usage of resource (CPU / GPU / storage / memory...) [%, MB...] <i>integrated to obtain site/RI-wide metrics</i> Total / partial (facility, IT, resource) energy consumption [kWh] Energy from given energy source (CO ₂ / renewable) [kWh] Carbon Intensity (CI) of electricity [kg CO ₂ /kWh] Water use for cooling (and source) [litres] Energy efficiency, utilisation/load levels of computing resource [%] General and domain-specific benchmarks [SERT, SPECpower, HEPsScore...] Internal temperature of servers and/or cooling systems CRAC/CRAH [°C] ASHRAE based metrics for Cooling system (e.g. Relative Humidity [%], Air temperature [°C]) Values from manufacturers/databases/LCA [kgCO ₂] Varies (e.g. depletion of abiotic resources such as water, minerals or metals, particulate matter...)	Tools used for calculation (power meter, IPMI, software, model...) Resources/elements included Certification/guarantee of energy and water provenance Provenance of carbon intensity table Definition and implementation of benchmarks Sensor system (and accuracy) Supporting infrastructure included Methods used for embodied calculation Hardware included in inventory System boundaries Methods used for impact calculation
ISO 14001/ISO 14004 Embodied carbon <i>CO₂ emissions associated w/ hardware lifecycle</i> Resource impact <i>Lifecycle Impact Assessment values</i>		

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