

Positive and Negative Impact of AI on the Environment

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Abstract. Based on the complete life cycle assessment framework, this paper quantifies both favorable and adverse environmental outcomes arising from the artificial intelligence sector. Intelligent tools can generate evident environmental benefits by optimizing energy allocation and advancing targeted climate governance initiatives. Nonetheless, rapidly expanding data infrastructure creates substantial ecological pressure, including considerable carbon footprints, excessive freshwater consumption and persistent electronic waste. This study selects a 1 MW data center as a typical research object. LCA calculation results indicate that power consumption serves as the dominant driver of carbon emissions throughout its whole operation cycle. Reconciling technological progress with environmental protection remains a prominent challenge. This research puts forward practical low-carbon transformation pathways for relevant facilities to cut resource use and advance stable and sustainable development of eco-friendly intelligent systems.

Keywords: artificial intelligence, life cycle assessment, data center, carbon emission

1. Introduction

In recent years, artificial intelligence has achieved rapid global development with booming market scale and user scale. In 2025, the total venture capital investment in the AI industry reached \$211 billion, representing a substantial year-on-year increase [1]. Driven by massive market demand, the scale of global data center infrastructure continues to expand. According to the statistics of the International Energy Agency (IEA), the number of global data centers has exceeded 11,000 by early 2024 [2]. In terms of user penetration, more than 1 billion people worldwide use independent AI tools in 2025, and Google's AI search-related services cover over 2 billion monthly active users [3].

From the perspective of industrial development, the United Nations Conference on Trade and Development predicts that the global AI market share will rise from 7% to 29% by 2033, becoming the dominant frontier technology [4]. McKinsey's research shows that the application penetration rate of generative AI in enterprises has increased from 33% in 2023 to 79% in 2025, and the popularization rate of comprehensive AI technology in enterprises has risen from 20% in 2017 to 88% in 2025, reflecting the comprehensive integration of AI into all walks of life [5].

AI technology has dual environmental values. On the positive side, it optimizes industrial energy consumption through data modeling, reduces redundant data processing and storage, and improves overall energy utilization efficiency [6]. Leading tech enterprises represented by Meta have actively laid out renewable energy projects, committed to 100% green energy supply, and promoted energy-

saving and efficient data center design through open source projects. In the field of environmental governance, AI can accurately predict power generation and carbon emission trends, optimize grid operation and energy allocation, and assist the formulation of scientific environmental protection policies, providing technical support for global low-carbon transformation.

On the negative side, the rapid expansion of the AI industry has brought severe ecological pressure. The whole industrial chain of AI involves mineral mining, electronic component manufacturing and large-scale data center operation. The surging demand for AI services drives continuous mineral exploitation, excessive energy consumption and water resource occupation [7]. Training a single large language model will produce more than 280 tons of carbon dioxide, equivalent to the lifetime carbon emissions of multiple vehicles. In addition, the rapid iteration of AI hardware equipment shortens the electronic product cycle, leading to a sharp increase in global electronic waste [8]. Heavy metals and organic pollutants in waste equipment penetrate into soil and water bodies, threatening ecological security and human health. The IEA predicts that the power consumption of global data centers will reach 620 to 1050 TWh in 2026, and the cooling water consumption of data centers has also become a prominent environmental problem in water-scarce regions [2].

2. Methodology

This study adopts the Life Cycle Assessment (LCA) method to comprehensively evaluate the environmental impact of AI data centers throughout their life cycle. LCA is a mature and widely used evaluation system in the field of sustainable research, which is applied to resource efficiency optimization and sustainable policy formulation in various industries [9]. It can quantitatively analyze the resource consumption and environmental emissions of research objects in the whole process of production, operation and scrapping.

The LCA framework adopted in this study includes four core links: goal and scope definition, life cycle inventory analysis, life cycle impact assessment, and result interpretation. This paper takes a 1 MW AI data center's one-year operation cycle as the research scope, and collects and quantifies the input and output data of materials, energy and water resources in the whole life cycle of data center construction, operation and equipment scrapping [9].

The core calculation formula for carbon footprint in this study is as follows:

$$E_{\text{total}} = \sum (\text{Mass}_i \times \text{EF}_i)$$

where E_{total} refers to the total life cycle carbon emissions of the data center, measured in kg CO₂e; Mass_i represents the consumption of the i -th material or energy resource in the life cycle; EF_i is the carbon emission factor corresponding to the i -th activity, which is used to convert resource consumption into equivalent carbon emissions [9].

3. Data sources and calculation basis

This study takes the annual operation data of a 1 MW AI data center as the basic research data, covering four core indicators: energy consumption, water consumption, IT equipment configuration and building area. All basic activity data and carbon emission factors are derived from authoritative industry reports and academic studies, with strong authenticity and credibility.

3.1. Basic activity data

Table 1. Resource statistics

Activity	Unit	Value	Source
Energy use	MWh	9636	IOP Science
Water use	m ³	67452	IOP Science
IT equipment	rack	37	AFCOM
Building structure	m ²	21277	Lawrence Berkeley National Laboratory

The annual power consumption of 9636 MWh is calculated based on 1 MW rated power and 8760 hours of annual operation, combined with the industry-standard power usage effectiveness multiplier of 1.1. The annual water consumption of 67452 m³ is obtained by matching the water usage effectiveness factor of 7 m³/MWh. The 37 IT racks are calculated according to the industry average high-density power distribution standard of 27 kW per rack. The building area is determined based on the empirical spatial data standard of megawatt-level data centers [10].

3.2. Carbon emission factor data

Table 2. Carbon emission factors

Activity	Unit	Value	Source
Energy use	kgCO ₂ /MWh	440	IOP Science
Water use	kgCO ₂ /m ³	0.53	IOP Science
IT equipment	kgCO ₂ /rack/year	11667	Energy Proceedings
Building structure	kgCO ₂ /m ² /year	24	Climate Accord

The power carbon emission factor conforms to the average carbon intensity standard of regional power grids. The water consumption factor covers the indirect carbon emissions generated in the process of water pumping, treatment and transportation. The IT equipment factor is the annual average embodied carbon converted based on the 3-year service life of high-density AI server racks. The building factor covers the whole-cycle carbon consumption of data center infrastructure construction and maintenance [10].

4. Results

According to the LCA quantitative calculation, the total annual carbon footprint of the 1 MW AI data center is approximately 5.22×10^6 kg CO₂e, and the emission contribution of each link shows obvious differentiation characteristics. Operational energy consumption is the dominant source of carbon emissions, reaching 4.24×10^6 kg CO₂e, accounting for 81.3% of the total footprint. The embodied carbon of building structures ranks second, with an annual emission of 5.11×10^5 kg CO₂e, accounting for 9.8% of the total. The embodied carbon of IT equipment accounts for 8.3% of the total emissions, with an annual output of 4.32×10^5 kg CO₂e. The indirect carbon emission of water consumption is the smallest, at 3.58×10^4 kg CO₂e.

The calculation results fully prove that the operational power consumption of AI data centers is the core ecological pressure source. A large number of global data centers rely on fossil fuel power generation for operation, and the backup diesel generators equipped for power failure emergencies will further increase carbon emissions [11]. With the continuous expansion of AI industrial scale, the superimposed environmental pressure of global data center clusters will further restrict the sustainable development of the digital economy.

5. Discussion and optimization strategies

To solve the ecological problems caused by the high energy consumption and high emission of AI data centers, this study proposes targeted low-carbon optimization schemes from the perspectives of cooling mode, energy supply and industrial mechanism, so as to realize the green transformation of AI infrastructure.

In terms of cooling optimization, traditional fresh water evaporative cooling consumes a huge amount of urban fresh water resources. Constructing data centers in coastal areas and adopting seawater direct cooling and deep water source cooling technology can completely replace municipal fresh water resources, reduce urban water resource pressure, and effectively reduce the indirect carbon emissions of water treatment.

In terms of energy structure optimization, matching on-site photovoltaic and wind power generation systems for data centers can realize zero-carbon power supply for IT equipment. Aiming at the intermittency of new energy power generation, supporting battery energy storage systems can build independent green microgrids to ensure the stable operation of high-load AI computing tasks. In addition, signing virtual green power purchase agreements can drive the large-scale development of regional renewable energy industries and realize the overall low-carbon layout of the AI industrial chain.

The above comprehensive optimization strategies can effectively reduce the power usage effectiveness and resource consumption intensity of AI data centers, balance the computing growth demand of the AI industry and ecological environmental protection, and provide a scalable technical path for the development of Green AI.

6. Conclusion

This paper adopts the Life Cycle Assessment method to quantitatively evaluate the whole-cycle environmental impact of a 1 MW AI data center, systematically analyzing the dual positive and negative environmental effects of artificial intelligence technology. The research confirms that AI is a double-edged sword for ecological governance: it can optimize energy allocation, improve environmental governance efficiency and promote low-carbon industrial transformation, while the high energy consumption, high water consumption and high carbon emission characteristics of its underlying data center infrastructure bring severe sustainable development challenges [2, 9].

Quantitative data shows that operational power consumption is the primary carbon emission source of AI data centers, occupying more than 80% of the total ecological footprint. The embodied carbon of buildings and equipment also constitutes non-negligible environmental pressure. To this end, this study proposes multi-dimensional optimization strategies such as seawater cooling, new energy matching and green power purchase agreements, which can effectively reduce the environmental burden of the AI industry.

In addition, this study has certain limitations. The research data is based on the standardized operation model of typical data centers, and there are differences in scale, equipment and energy

structure of different data centers, resulting in certain data simplification errors. Subsequent research can further optimize the evaluation model according to regional differences and equipment iteration, so as to build a more accurate Green AI environmental impact assessment system.

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