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Examining the Environmental Impact of High-Powered Computing

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Abstract

In parallel with the notable contributions of high-performance computing (HPC) to advancements in research, industry, and digital infrastructure, its surging energy demands and associated carbon footprint have emerged as pressing environmental concerns. Recent projections suggest that, without appropriate intervention, global electricity usage by data centers could surge by up to 160% by 2030, posing a major obstacle to achieving carbon neutrality. To confront this issue, this paper introduces a quantitative and layered assessment framework that evaluates the carbon emissions of HPC systems, factoring in operational intensity, regional deployment patterns, and power grid composition. Furthermore, it integrates water consumption analysis arising from cooling mechanisms to establish a dual-focus environmental indicator system that highlights both carbon and water-related impacts. Simulation results suggest that even under moderate usage rates (e.g., 56.25%), annual carbon emissions could exceed 290 million metric tons, and potentially reach over 500 million tons if energy structures worsen. Hence, accelerating the shift towards renewable and clean energy emerges as a vital trajectory for sustainable HPC development

Keywords

Carbon Emissions; High-Performance Computing (HPC); Environmental Protection.

1. Introduction

As frontier technologies-including With the continuous progress of technologies such as artificial intelligence, big data, climate modeling, and blockchain, high-performance computing (HPC) systems have rapidly proliferated worldwide, becoming essential tools in driving forward scientific discovery, streamlining industrial workflows, and enabling smarter social infrastructures [1]. Yet, the environmental cost of such progress, especially in the form of elevated electricity demand and carbon discharge, has become increasingly difficult to overlook[2]. According to Goldman Sachs the global energy consumption of data centers may reach 2.6 times today's level by 2030, raising profound concerns for international climate policy.

The primary environmental challenge associated with HPC lies in its intensive power requirements. Given the heavy reliance on fossil fuels in many regions, the operation of these systems results in substantial greenhouse gas emissions[3]. Carbon output varies notably by geography due to differences in energy sourcing; for instance, countries like China and Poland, which depend heavily on coal-fired electricity, experience particularly high emission intensities[4]. Furthermore, secondary burdens' including water use for system cooling, e-waste accumulation, rare-earth metal depletion, and ambient noise-collectively amplify the ecological footprint of HPC facilities.

In response to the above issues, this paper constructs a multi-level, quantifiable HPC carbon emission assessment model, comprehensively considering factors such as equipment power, utilization rate, geographical distribution, and energy structure, to estimate the annual carbon

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emission levels under different scenarios. It further extends to water resource consumption, forming a "carbon emission - water pressure" dual-index assessment framework. On this basis, this paper conducts scenario simulation analysis to explore the mechanism of the impact of different energy combinations and utilization rate changes on the environment, and proposes practical and feasible green transformation paths and policy recommendations, with the aim of providing theoretical support and decision-making basis for the sustainable development of global HPC.

2. Model Construction

2.1. Model Overview

2.1.1. Model Design Concept

As HPC systems rapidly expand in scale and capacity, the corresponding energy demand has escalated, primarily due to their dependence on electricity grids still dominated by fossil energy sources[5]. This dependence has made carbon emissions a key environmental concern associated with high-performance computing[6]. To quantify such impact, this study proposes a hierarchical evaluation model, which captures multiple dimensions of HPC-related carbon output through the following structure:

(1) Device-level simulation: Two operational scenarios-full capacity and average utilization-are considered to estimate electricity usage across different categories of HPC equipment.

(2) Geographical distribution modeling: Total energy consumption is disaggregated by region, based on the current global allocation of HPC infrastructure.

(3) Emission conversion layer: Regional carbon output is calculated by matching local power mix profiles with standardized emission coefficients.

(4)Scalability and adaptability: The framework is designed to incorporate additional ecological metrics, such as cooling water use and spatial footprint, facilitating broader environmental analysis.

Overall, the model delivers a quantitative foundation for supporting the transition to more sustainable computing practices and informing policy development.

2.1.2. Variable Selection and Definition

To enhance both the scientific rigor and practical applicability of the carbon emission model for HPC systems, this study adopts the framework proposed by Ahmed and Verma, and classifies the core variables into three principal dimensions: operational characteristics of hardware, spatial deployment profiles, and emission factor mappings. These dimensions align with the model's underlying logical tiers, namely computational energy behavior, regional distribution, and source-based emission intensity.

Computational energy behavior: Different categories of HPC nodes display varied levels of energy consumption depending on their design power and average utilization.

Geographical allocation: Regional differences in electricity generation result in distinct energy usage proportions for identical computing systems across different locations.

Emission intensity of energy mix: Each energy source type (e.g., coal, gas, renewables) yields a specific amount of carbon per unit consumed, thus contributing differently to the system's environmental footprint.

2.1.3. Model

(1) Energy Consumption Behavior

Table 1. Symbol Description Of Energy Consumption Behavior

Symbol	Definition	Unit	Interpretation
P_i	The power levels of the devices in category i	kW	Design power limiters for different high-performance computing nodes (such as CPU nodes, GPU nodes)
μ_i	The average utilization rate of the equipment in category i		Actual operating ratio hours to maximum possible hours
N_i	The global total quantity of equipment in category it	number	The projected total deployment quantity of various high-performance computing hardware nodes
t	Annual running time	hour	It is usually calculated based on 8,760 hours (continuous operation throughout the year)

Based on Table 1, the annual electricity consumption of global high-performance computing systems is jointly determined by these variables, which are interrelated and mutually influential. The formula for calculation is presented as follows:

$$E = \sum_{i}^{n} P_i \cdot \mu_i \cdot N_i \cdot t \tag{1}$$

By aggregating the energy consumption of various types of high-performance computing devices, this formula accomplishes bottom-up energy consumption estimation, thus obtaining the total annual energy consumption (measured in kilowatt-hours) as the initial step for calculating carbon emissions.

(2) Spatial distribution

As shown in Table 2, given that global high-performance computing is distributed unevenly across various regions rather than being centrally deployed, and considering the diverse energy compositions and varying proportions in different areas, it becomes essential to allocate the overall energy consumption among countries or continents in a reasonable manner, thereby reflecting the regional disparities in carbon emissions resulting from distinct energy usage patterns[7]. This regional allocation allows the model to additionally integrate the disparities in energy composition across different regions, thus establishing a linkage with carbon emissions.

Table 2. Symbol Description Of Spatial Distribution

Symbol	Definition	Unit	Interpretation
R_j	The percentage of high-performance computing operations or devices in region j		Indicating the proportion of this region in the global high-performance computing resources
E_j	Energy consumption of region j	kWh	According to the proportion of total energy consumption, this formula: $E_j = R_j \cdot E$

(3) Carbon emission conversion variables

As shown in Table 3, by introducing carbon emission coefficients specific to each type of energy, we have established a mapping mechanism from energy consumption to carbon emissions, thereby converting electricity consumption into carbon emissions.

ISSN: 2710-0723

Table 3. Symbol Description Of Carbon Emission

Symbol	Definition	Unit	Interpretation
ϕ_{jk}	The proportion of energy type k in region j		Example: 30% coal, 40% natural gas, 20% wind, etc. in the U.S. power grid
γ_k	Carbon coefficient of energy type k	$kgCO_2$ /kWh	The carbon emission intensity generated by the energy consumption of different energy sources

In this context, the formula for regionally estimating carbon emissions is:

$$C_j = E_j \cdot \left(\sum_k \phi_{jk} \cdot \gamma_k\right) \tag{2}$$

The weighted outcome of each region's power supply structure and the carbon intensity associated with each energy type is effectively demonstrated by this formula. The impact of each region's energy structure on the carbon emission level is genuinely reflected in this finding.

The global carbon emissions :

$$\mathrm{C} = \sum_{\mathrm{j}} \mathrm{C}_{\mathrm{j}} \tag{3}$$

Units: Mt (1Mt=1,000,000 tonnes=10^9kg)

The global annual total carbon emissions resulting from the operation of the high-performance computing system are obtained by aggregating the carbon emissions across all regions. This data can be used as an indicator for quantitative assessment of environmental impacts.

2.2. Model Assumption

To maintain both computational feasibility and model transparency, a set of practical and streamlined assumptions was established during the initial modeling stage. These assumptions aim to simplify the model's structure while focusing on the most critical environmental consequence of high-performance computing systems-namely, their energy consumption and the resulting carbon emissions[8]. Although these assumptions offer valuable guidance for real-world applications, they also leave flexibility for future refinements, enabling the model to be expanded or adjusted for sensitivity studies. One such assumption is that all high-performance computing systems are considered to operate continuously for a total of 8,760 hours annually.

First and foremost, it is assumed that the high-performance computing system functions continuously throughout the entire year, operating uninterruptedly for 365 days per annum, 24 hours per day, with its annual operational duration being:

The common practice of large data centers operating "around the clock" is reflected in this assumption. Although a certain proportion of equipment may cease to function properly in practice due to maintenance requirements, malfunctions, and other factors, this proportion remains relatively small and exerts an insignificant influence on the aggregate energy consumption.

The power of each device is a predetermined fixed rated value.

Assuming that the value remains constant over time, each type of high-performance computing node is assigned a fixed power value in this model. Although operating load and thermal efficiency are among the factors that influence actual power consumption, employing fixed power values can serve as an approximate representation of equipment power demand in large-scale modeling scenarios.

The average utilization rate for each device has been established as the reference average value derived from industry research:

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Assuming that it will remain stable throughout the entire year, we set the equipment utilization rate as a fixed value. Applicable to the estimation of large-scale systems, this average processing method not only simplifies the model but also allows for further refinement based on regions or types in practical applications.

According to the predetermined arithmetic ratio, allocate high-performance computing resources at the global level to each region in a well-organized manner.

Considering the substantial regional disparities in global high-performance computing facilities, particularly the dominance exhibited by the United States, China, Japan, and Europe, it is assumed that the resources of these computing systems are distributed across different regions based on a predetermined arithmetic allocation ratio. This ratio serves to allocate the aggregate global energy consumption across diverse regions, thus incorporating a regional dimension into the estimation of carbon emissions.

The energy structure in each region exhibits short-term stability without significant changes:

During the model analysis period , it is assumed that the energy structure of power generation in each region will remain constant, excluding the influence of seasonal variations or transient policy modifications. Although the energy structure will undergo gradual optimization over time, this assumption guarantees that the variables involved in short-term forecasting remain controllable while ensuring computational clarity.

Assuming the carbon factor values of each energy source stay constant:

Assuming that the carbon intensity per unit of each energy type remains constant, we consider it to be independent of regional variations, seasonal changes, or power generation efficiency. Usually, these carbon factor data are sourced from the International Energy Agency (IEA) or derived from the comprehensive climate reports issued by the United Nations.

3. Model Application and Simulation

Based on the carbon emission assessment model established in Chapter 2, this chapter conducts a quantitative simulation of the annual carbon emission levels of global high-performance computing (HPC) systems in 2024. By integrating real statistical data with future development predictions, it further forecasts the emission change trends until 2030, providing data support for subsequent scenario analysis and the formulation of emission reduction measures. During the simulation process, we designed two scenario plans, representing different energy structures and usage proportions, to reflect the maximum and minimum scenarios of the environmental impact of HPC systems. This setting lays the foundation for proposing targeted emission reduction suggestions.

3.1. Estimated Carbon Emissions in 2024

3.1.1. Initial Parameter Setting

-Number of global HPC systems(nodes): N=3900000 [3]

-Node rated maximum power: P=30kW [4]

-Annual operating time: t=8760h

-Average utilization: u=56.25% [4-2]

Then the global annual energy consumption is:

$$E = P \cdot u \cdot N \cdot t = 30 \times 0.5625 \times 100000 \times 8760 = 1.4775 \times 10^{10}\ \text{kWh} \tag{4}$$

3.1.2. Energy Mix and HPC Share in Six Continents

For the purpose of enhancing data collection efficiency, we categorized the global landscape into six distinct regions: Africa, Asia, South America, North America, Europe and Oceania. Simultaneously, we conducted an analysis on the four most significant energy structures

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globally. Based on their power distribution in high-performance computing (HPC) and energy structure, the subsequent settings were established, as shown in Table 4.

Table 4. Energy Distribution

Region	Oil (31%)	Coal (27%)	Natural Gas (24%)	Renewables (11%)
Africa	26%	13%	11%	11%
Asia	23%	49%	13%	11%
Europe	36%	27%	20%	6%
North America	35%	16%	30%	8%
Oceania	32.3%	13.5%	27.4%	24.5%
Latin America	38.9%	25.9%	25.5%	9.4%
Average Share	31.87%	24.07%	22.20%	11.65%
Unit Emission Factor	0.74	0.95	0.47	0.02

3.1.3. Regional Carbon Emission Estimation Process

Formula

$$E_j = R_j \cdot E \tag{5}$$

$$C_j = E_j \cdot \left(\sum_k \phi_{jk} \cdot \gamma_k\right) \tag{6}$$

The final result is the total global carbon emissions:

$$C = \sum_j C_j = C_{Aisa} + C_{NA} + \cdots + C_{Africa} \tag{7}$$

Based on the data and the formula We use R to get result:

(1) Full capacity: 528036.8 MT

(2) Average Utilization: 297020.7 MT

This figure represents the direct carbon emissions generated by global high-performance computing systems in 2024, and also serves as a benchmark for the projections for 2030.

3.2. Effects of Shifts in Energy Composition and Demand on Future Estimates

The swift growth of the high-performance computing sector, alongside the enforcement of various environmental initiatives, is anticipated to bring about notable alterations in energy composition and its regional allocation. To evaluate their influence, a systematic framework will be used to simulate how three categories of such changes affect future model estimations.

3.2.1. Hydrogen on Board: An Additional Clean Energy Category

Assuming that 3% of the global power grid's electricity will come from hydrogen energy by 2030 (with a carbon emission coefficient of 0.01), then the new weighted carbon emission coefficient for each region will be:

$$\gamma_j' = 0.97 \cdot \gamma + 0.03 \times 0.01$$

For example, the carbon factor changes in the Asian region are:

$$\gamma_{Aisa}' = 0.97 \cdot 0.65 + 0.03 \times 0.01 = 0.6302$$

Based on the data and the formula We use R to get result:

(1) Full capacity: 451106.4 Mt

(2) Average Utilization: 253747.4 Mt

In conclusion, the introduction of energy sources with lower carbon emission coefficients, such as hydrogen, will lead to a significant reduction in carbon dioxide production when compared to the original energy structure. To a certain extent, enhancing the utilization and broadening the application scope of hydrogen energy can play a protective role in environmental conservation.

3.2.2. Increasing the Proportion of Renewable Resources

Based on the proportion of renewable energy sources, we increased the share of renewable energy by approximately 10% (accounting for about 20% of the total), while reducing the share of coal by approximately 10% (accounting for about 20% of the total). This was done to investigate the changes in global carbon dioxide emissions. The results show that:

(1) Full Capacity: 455217.5 Mt

(2) Average Utilization: 256059.9 Mt

Making rational use of renewable resources can reduce the environmental impact of high-performance computing. We have divided the proportion of resources to be used from renewable sources into three categories:

Scenario 1: The share of renewable resources remains unchanged

Scenario 2: A gradual increase in the share of renewable energy sources

Scenario 3: Full reliance on renewable resources (as a theoretical extreme)

To illustrate how renewable energy adoption benefits the environment, we have developed corresponding visual materials to effectively convey the outcomes,as shown in Figure 1.

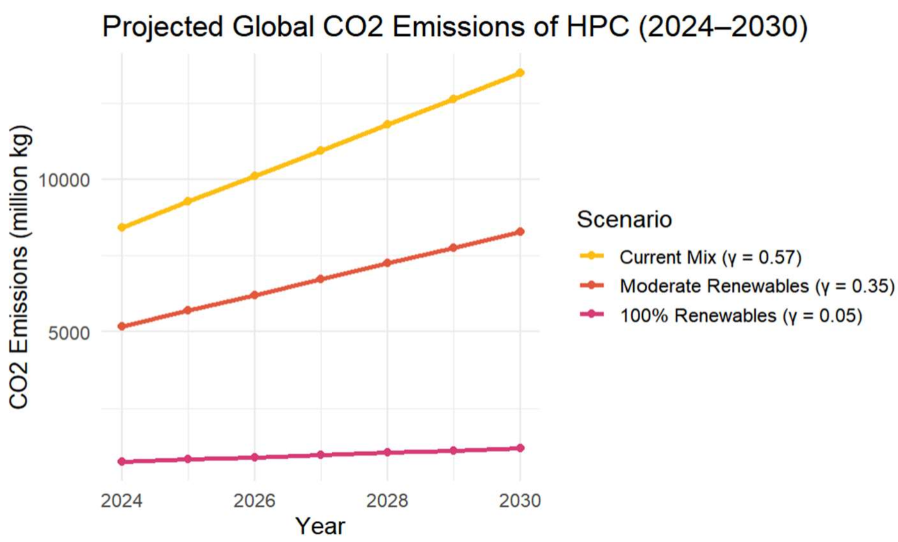

Figure 1. Carbon Emission

In conclusion, increasing the proportion of renewable energy can lead to a reduction in carbon emissions, with an impact comparable to that achieved by enhancing hydrogen energy utilization. Both approaches aim to reduce the share of carbon-intensive energy within the overall energy portfolio.

ISSN: 2710-0723

3.2.3. Increased HPC Energy Demand

The surge in energy demand can be attributed to: rapid technological advancements, a proliferation of high-performance computing devices, an increased share of high-performance computing in energy consumption across six continents, and enhanced power utilization efficiency of high-performance computing systems. According to the literature, with an energy growth rate of 10%, it can be inferred that the energy demand in 2030 will reach 160% of the 2024 level. The R results:

(1) Full Capacity: 844858.8 Mt

(2) Average Utilization: 475233.1 Mt

A significant environmental impact can be anticipated as the increase in energy consumption by high-performance computing inevitably leads to a noticeable rise in carbon dioxide emissions. We might need to formulate plans to prevent this from happening.

3.3. Projected 2030 Range

In earlier sections, the model primarily examined the effect of individual variables in isolation. However, real-world scenarios require the joint consideration of multiple factors. Therefore, the following analysis integrates various energy compositions, allocation ratios, and levels of energy demand from high-performance computing (HPC) to simulate two boundary scenarios, offering a broader perspective on the potential environmental footprint of HPC systems.

3.3.1. Scenario Delineation and Description

We present two cases in Table 5 for comparison and analysis.

Table 5. Two Cases

Case	descriptive	Parameter changes
P_1	The reliance on fossil fuels in the energy structure has increased, the number of high-performance computers has risen, and energy demand has grown to 160% of its original level	The energy structure is even less environmentally friendly: it has added resource A (with a carbon emission coefficient of 0.65 and a proportion of 10%), resulting in a higher carbon emission coefficient and an energy multiplier of 1.6
P_2 (green contraction type)	Increase the use of renewable energy and introduce clean energy B. Reduce energy demand to 90%	Energy substitution solutions for reducing emissions: Resource B (carbon emission coefficient 0.05, accounting for 5%), its carbon emission coefficient has decreased, and the energy multiplier is 0.9

Variation:

γ_j :carbon factor

E :Energy multiplier

ϕ_{jk} :Percentage of energy mix

We get two sets of predicted carbon emissions:

$$C_{P_1} = 1.6 \cdot E \cdot \gamma_{P_1}$$

$$C_{P_2} = 0.9 \cdot E \cdot \gamma_{P_2}$$

R results:

(a) Full Capacity: (375828 ,1015594) Mt

(b) Average Utilization: (211403.2, 571271.8) Mt

ISSN: 2710-0723

3.3.2. Interpretation of Results

According to the simulation, under scenario P1, despite advancements in technology that have steadily enhanced computing capabilities, carbon emissions are projected to remain well above 2024 levels if the energy mix is not properly optimized. In contrast, scenario P2 demonstrates that with widespread adoption of low-carbon energy sources and effective implementation of energy-saving strategies, it is possible to boost computing performance while maintaining control over carbon output. These two scenarios collectively illustrate the potential variation in carbon emissions by 2030, offering a quantitative foundation to inform future policy development.

4. Model Analysis and Optimization

In the previous analysis, we mainly established a hierarchical model of annual carbon emissions for HPC systems based on power consumption. However, the impact of HPC systems on the environment goes far beyond carbon emissions; it also involves water resource consumption, electronic waste, land occupation, and chemical pollution, among other aspects. To further enhance the applicability and completeness of the model in environmental comprehensive assessment, this chapter will introduce a calculation module related to water resource consumption on the basis of the original model. By combining carbon emission indicators, a more comprehensive assessment of the environmental impact of HPC systems will be conducted from the dual perspectives of water and carbon, and the intrinsic mechanism of the internal relationship between water resource usage and energy consumption will be deeply explored.

4.1. Motivation for Expanding the Model: Integrating Water Usage Considerations

4.1.1. Rationale for Selecting Water Resources as an Extension Focus

that the cooling infrastructure in HPC data centers plays a central role in driving water usage:

Large data centers mainly rely on evaporative cooling towers and liquid cooling systems to maintain the operating temperature of the equipment.;

There are significant regional differences in water resource consumption: for instance, areas that are arid or suffer from water scarcity are subjected to greater environmental pressure;

The water cooling system is closely related to power consumption and has good model coupling characteristics.

4.1.2. Supplementary Units

Symbol of Water Consumption as shown in Table 6.

Table 6. Symbol of Water Consumption

Symbol	Definition	Unit	Interpretation
ω_j	Water consumed per unit of electricity consumption in region j	L/kWh	Response of regional water intensity per unit of electricity consumption
W_j	Total annual water consumption in region j	L	Area water use for cooling
W_{global}	Total water consumption	L	Global aggregated results
R_j	The proportion of region j in the total global energy consumption for high-performance computing		Probability

4.1.3. Additional Assumptions

Cooling water usage exhibits a linear correlation with energy consumption

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$$W_j = \omega_j \cdot E_j \tag{8}$$

Among them, W_j denotes the total annual water usage in the specified region (measured in liters), while ω_j indicates the local coefficient of cooling water consumption (unit: L/kWh).

The coefficient remains constant for the region, reflecting the prevailing cooling technologies and environmental conditions, and is assumed to be unaffected by seasonal changes.

This model focuses solely on the direct water usage associated with cooling systems, omitting indirect sources such as those related to equipment cleaning, heating processes, and other auxiliary operations.

At this stage, the model does not incorporate constraints on water resources or feedback mechanisms. It is presumed that each region has adequate water supply capacity, ensuring that cooling operations proceed without limitation.

$$W_j = \omega_j \cdot E_j = \omega_j \cdot R_j \cdot E \tag{9}$$

$$\mathrm{W} = \sum_{\mathrm{j}=1}^{\mathrm{M}} \mathrm{W_j} \tag{10}$$

4.2. Extended Model Analysis and Implications

4.2.1. Embodiment of Spatial Differences

As shown in Table 7, among different regions, significant disparities can be observed in the efficiency of water resource utilization and the technologies employed for water usage. Upon the introduction of this model, it becomes possible to identify dual high-risk areas marked by "high carbon emission intensity and substantial water consumption," thereby offering a scientific foundation for environmental oversight and the strategic placement of data centers.

Table 7. Water Consumption In Different Region

Region	ω_j	R_j	Relative Water Stress Level
Asia	2.2	35%	High
Europe	1.5	20%	Medium
Africa	2.5	5%	Extremely High

4.2.2. Integration of Multidimensional Environmental Indicators

Table 8. Symbol Of Global Water Consumption

Symbol	Definition	Unit	Interpretation
$\mathrm{C_{ref}}, \mathrm{W_{ref}}$	Standardized reference value		Water consumption for regional cooling
EI_{global}	Global Environmental Impact Index		Global summary results
λ_C, λ_W	The relative proportion of carbon and water		Carbon and water have different weights in terms of their impact on the environment.

Table8 is the Symbol Of Global Water Consumption.By forming a dual indicator system for environmental burdens, carbon emissions and water resource consumption enable a multi-dimensional evaluation of the environmental impact arising from data center operations. For instance, a holistic indicator can be developed:

$$\mathrm{EI_{global}} = \lambda_C \cdot \frac{\mathrm{C_{global}}}{\mathrm{C_{ref}}} + \lambda_W \cdot \frac{\mathrm{W_{global}}}{\mathrm{W_{ref}}} \tag{11}$$

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This model can assist us more effectively in comprehensively assessing the environmental impact caused by the carbon emissions and water consumption of high-performance computers. The greater the value, the more significant the environmental burden becomes; conversely, a smaller value suggests that certain effective measures have been implemented, thus providing varying degrees of environmental protection.

5. Conclusion

With the widespread application of high-performance computing (HPC) systems in fields such as artificial intelligence, climate simulation, and big data, the environmental issues brought about by them have become increasingly prominent. This paper focuses on the high energy consumption and high carbon emissions of HPC systems, and constructs a multi-level, scalable carbon emission and water resource consumption assessment model. It systematically quantifies the environmental impact under different operating efficiencies and energy structures, and proposes feasible emission reduction paths through scenario simulations.

The research found that even at an average utilization rate of 56.25%, the global annual carbon emissions of HPC systems in 2024 would still reach approximately 297 million tons; if the future energy structure deteriorates, this value could exceed 500 million tons, highlighting its significance in the global carbon governance system. Based on this, this paper further introduces the water consumption factor and constructs a "carbon-water" dual-index assessment framework. The results show that regions such as Asia and Africa, due to their high carbon intensity and water consumption, constitute typical environmentally high-risk areas and require priority green intervention.

In the scenario simulation of energy structure and computing power expansion, the research shows that: if the proportion of renewable energy can be increased, hydrogen energy can be introduced, and the hardware energy efficiency and cooling technologies can be optimized, even if the scale of HPC computing power continues to expand, carbon emissions can be effectively controlled, providing quantitative support for achieving "high computing power and low emissions".

Furthermore, this paper also summarizes the multi-dimensional impacts of HPC on the environment, including carbon emissions, water consumption, electronic waste, rare resource extraction, air pollution, chemical usage and energy usage inequality, etc. Although some aspects were not included in the core model, the structural framework constructed in this paper provides a theoretical basis for subsequent comprehensive modeling and governance evaluation.

In conclusion, the environmental assessment model proposed in this paper has excellent operability and adaptability. It can not only be used for assessing the current pressure of HPC systems, but also provides model tools and decision-making basis for the formulation of green computing power policies, the location selection of data centers, and international sustainable development cooperation in the future.

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