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Examining the Environmental Impact of High-Powered Computing

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Abstract:

In recent years, the popularity of high-performance computing (HPC) has made its environmental impact increasingly prominent. The operation of HPC equipment generates ecological problems such as air pollution, water wastage, and solid waste pollution, posing a serious threat to ecosystems and human health. This study aims to develop a broad model to assess the environmental impacts of carbon emissions, cooling water resources required, and e-waste generated during HPC operation. The ecological effects of HPC in terms of atmosphere, water resources, and solid waste were assessed through the model. We suggest technical and policy solutions designed to enhance energy efficiency, boost the share of renewable energy sources, refine the placement of data centers, encourage sustainable supply chains, and strengthen e-waste recycling programs. It highlights the criticality of the environmental impact of HPC and presents our research insights and recommendations to support global efforts to achieve sustainable development.

Keywords: High-powered Computing (HPC); Environmental Impact; Carbon Emissions; Policy Recommendations.

1 Introduction

In today's digital era, high-powered computing (HPC) has become an essential tool with profound implications across various sectors[1]. HPC systems can execute complex calculations and simulations at exceptional speeds, driving advancements in scientific research, engineering, and many other fields. These systems are critical for applications like weather forecasting, climate modeling, drug discovery, and aerospace design, which are pivotal in deepening our understanding of the world and fostering innovation.

As the pace of society accelerates and HPC capabilities continue to evolve, there is a quest for more powerful and efficient computing resources. That has led to establishment of large-scale HPC centers, often equipped with thousands of processors, which consume vast amounts of energy. The energy consumption of HPC systems is costly regarding resources and raises various environmental issues. On the one hand, most of the energy supplying HPC operations comes from fossil fuel power plants, and burning fossil fuels contributes to greenhouse gas emissions and climate change. On the other hand, manufacturing and maintaining large computer systems and even discarded parts generate large amounts of e-waste. Improper disposal of this e-waste releases various toxic substances into the environment, polluting ecosystems and affecting the safety of biological life. Additionally, the cooling requirements of HPC systems further impact the environment. The substantial energy needed for cooling can increase overall energy consumption and carbon emissions.

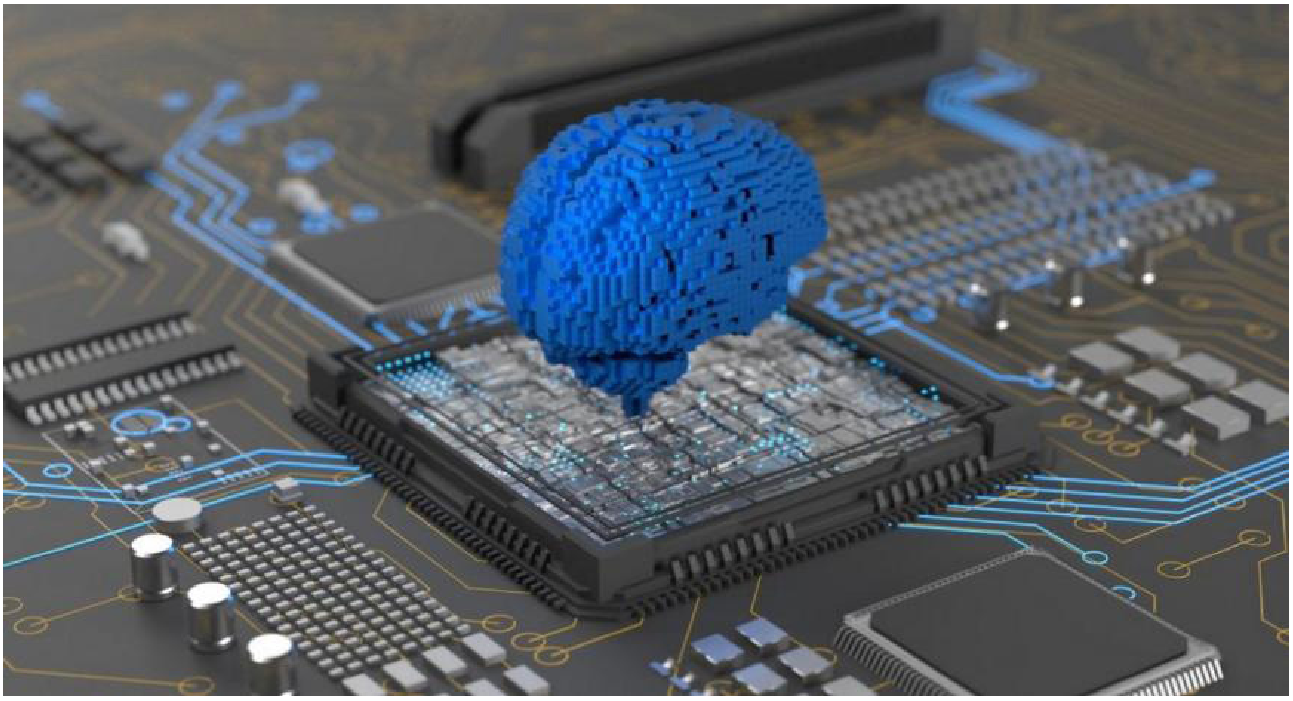

Fig. 1 High-Powered Computing

In this paper, the following the following works is studied to analyze the environmental impacts of HPC:

Firstly, we predicted the global demand for computing power and established the relationship between the demand for computing power and the actual reserve computing power, the computing cluster capacity. After the above definition, we set the concept of computing cluster entire power operation and half power operation as entire load operation and average utilization rate and collected relevant data on HPC worldwide. We planned a series of formulas from computing power prediction to computing cluster quantity, from computing cluster quantity to computing cluster energy consumption, and from computing cluster energy consumption to calculating the carbon dioxide emissions caused by cluster energy consumption.

Secondly, we utilized the global high-tech related data we previously found to input into the formulas corresponding to questions 1 and 2 and combined the prediction of global computing power with the above formulas to provide the impact of HPC on carbon dioxide emissions around 2030.

Thirdly, the impact of increase of the proportion of renewable energy is studied. In the model, we estimated the proportion of energy occupied by renewable energy in the future based on previously queried data and calculated the corresponding carbon emission reduction under the optimistic and pessimistic conditions of new energy development. We also improved the model's description of environmental impact by establishing high-powered calculations for other key areas, such as water resources and land occupation.

Fourthly, we developed a solution that included technology and policy guidance. If our suggestions were adopted, we would merge the impacts of technology and policy guidance into the model by reducing the carbon dioxide emission coefficient per unit of energy consumption.

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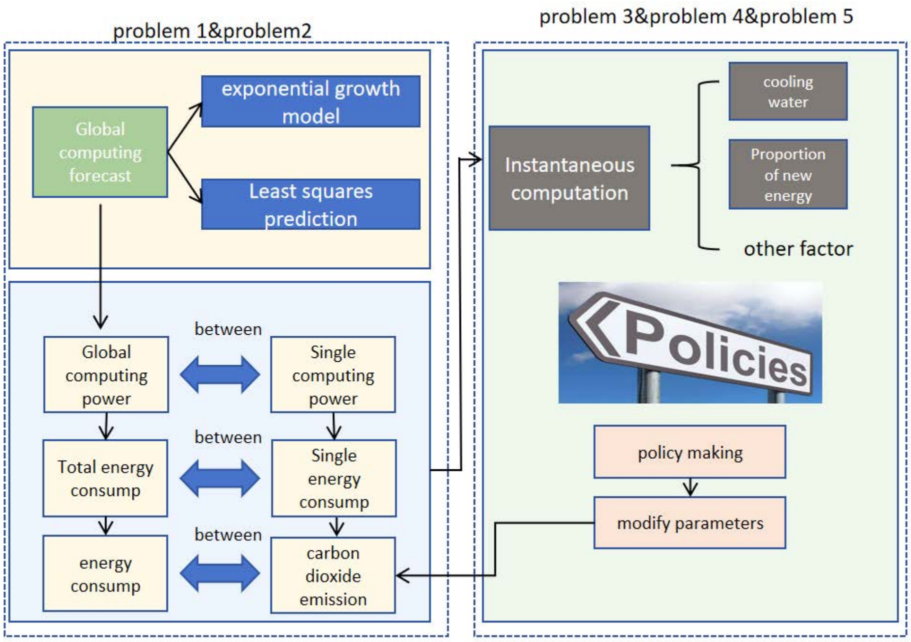

Fig. 2 Model Overview

2 Modeling Compute Resource Demand

2.1 Data Description

(1) According to the "2023-2024 Global Computational Power Demand Development Report" [2] released by the International Data Corporation (IDC) and Inspur Information, the report provides the computational power demand data for Global from 2018 to 2022. The specific data are as follows:

Table 1 Computational Power Demand

Year	Computational Power Demand (EFLOPS)
2018	286.66
2019	395.66
2020	546.04
2021	754.38
2022	906.00

2.2 The Establishment of Computational Power Demand

2.2.1 Data Fitting Principles

Data fitting is a statistical method to find a mathematical model that best describes a given dataset. The basic principle of data fitting is determining the model's parameters by minimizing the error between the model's predicted values and the actual observed values.

Error functions can visually model the difference between predicted values and actual observations. Common standard error functions include the following.

(1) Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

(2) Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

(3) Maximum Error:

$$\text{MaxError} = \max_i |y_i - \hat{y}_i| \tag{3}$$

2.2.2 Fitting Process

We use the data from Table 1 and apply linear, quadratic, and exponential fitting. We analyze the mean squared error (MSE) for each model to determine the optimal fitting function, and the results are shown in Table 2.

Table 2 MSE of the Fitting Functions

Fitting Method	Mean Squared Error (MSE)
Linear	534.64
Quadratic	241.69
Exponential	87.73

The fitting results for the three functions are shown in Figure 3.

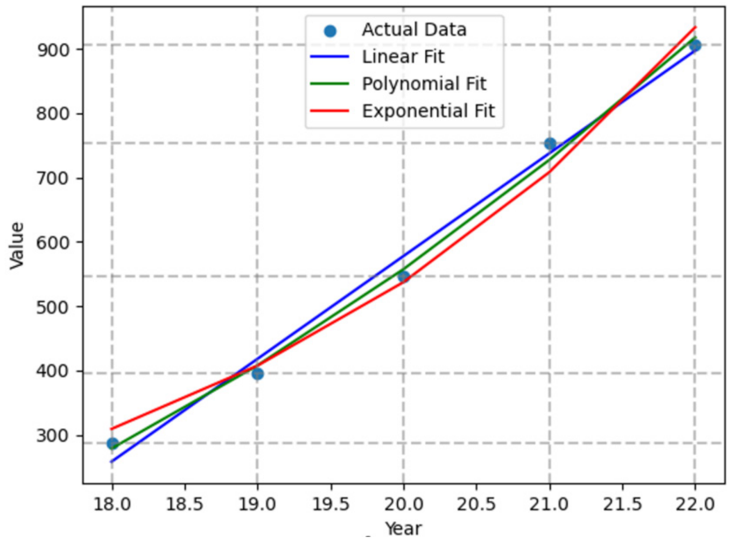

Fig. 3 Fitting Results for the Three Functions

Ultimately, we adopt the exponential fitting function as the global computational power prediction model. The fitting result is:

$$f(t) = 2.1382 \times exp(0.2763 \times t) \quad (4)$$

$f(t)$ is the global computational power for year t, and t is the year; if we predict 2027, then t is 27.

3 Computational Power and Carbon Footprint

3.1 Term Definitions

Full capacity describes the energy consumption of the HPC system when it is running at its highest computational performance.

Average Utilization Rates refers to the energy usage of the HPC system under normal operating conditions, considering that the system is not always running at maximum load[3].

3.2 Computational Power Requirement 64 Core CPU

The relationship can be expressed as:

$$F = a \times f \times e \quad (5)$$

where: F represents the theoretical floating-point performance (floating-point operations Per Second) of the 64core CPU, a represents the number of CPU cores, 64, f represents the CPU operating frequency, and e represents the number of floating-point operations executed per clock cycle. After reviewing the manual[4], the following table has been compiled:

Table 3 Specifications of the Latest Server CPUs from Intel and AMD

Number	Manufacturer	Model	CPU Core Count	Base Frequency (THz)
1	AMD	7713 Single Socket	64	2.0
2	AMD	7763 x2	128	2.45

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Number	Manufacturer	Model	CPU Core Count	Base Frequency (THz)
3	AMD	7513 x2	64	2.6
4	AMD	7K83 x2	128	2.45
5	AMD	7543 Single Socket	32	2.8
6	AMD	7413 x2	48	2.65
7	AMD	7313 x2	32	3.0
8	AMD	7543 x2	64	2.8
9	Intel	6338 x2	64	2.0
10	Intel	6348 x2	56	2.6
11	Intel	8380 x2	80	2.3
12	Intel	6342 x2	48	2.8
13	Intel	4310 x2	24	2.1

Considering the average value for CPU frequency (*f*):

$$\bar{f} = \frac{1}{N}\sum_{i=1}^{N} f_i \tag{6}$$

where $\bar{f}$ represents the average of the CPU's operating frequencies, N represents the number of types of CPUs listed in Table 3, and f_i represents the operating frequency of the i-th CPU. We remove the highest and lowest values and then calculate the average frequency of CPUs.

$$\sum_{i=1}^{13} f_i = 2.45+2.6+2.45+2.8+2.65+2.8+2.0+2.6+2.3+2.8+2.1=28.45 \tag{7}$$

$$\bar{f} = \frac{28.45}{13} \approx 2.586THz \tag{8}$$

To simplify, we assume that each brand's number of floating-point operations per clock cycle is the same. After querying, AMD and Intel have approximately 16 FLOPs per clock cycle. Therefore, in Equation (5), f is taken as 2.586 THz, e is taken as 16, and the computing power requirement for a 64-core CPU is:

$$F = 64 \times 2.586 \times 16 = 2648.064TFLOPS \tag{9}$$

3.3 The power consumption of a 64-CPU

We establish the relationship between power consumption and computational demand using the dynamic power and frequency relationship as follows:

(1) Dynamic Power and Frequency Relationship

In digital circuits, dynamic power mainly results from the charging and discharging of capacitors. Dynamic power can be represented as:

$$P_{dynamic} = C \cdot V^2 \cdot f \tag{10}$$

C is the load capacitance, V is the supply voltage, and f is the operating frequency.

(2) Computational Demand and Frequency Relationship

Computational demand (FLOPS) is usually proportional to frequency:

$$F = a \times f \times e \tag{11}$$

Therefore,

$$F \propto f \tag{12}$$

(3) Relationship Between Power Consumption and Computational Deman

Combining the above two relationships, we get:

$$P_{dynamic} = C \cdot V^2 \cdot \left(\frac{F}{a \times \mathrm{e}}\right) \tag{13}$$

(4) Considering Static Power Consumption

In addition to dynamic power, static power must also be considered. Static power primarily stems from leakage current, generally independent of frequency but depends on temperature and process node. Therefore, the total power can be expressed as:

$$P_{64cpu} = P_{static} + P_{dynamic} \tag{14}$$

Assuming static power is a constant, then:

$$P_{64cpu} = C_0 + C \cdot V^2 \cdot \left(\frac{F}{a \times \mathrm{e}}\right) \tag{15}$$

where, $C_0 = 0.002\mathrm{w}$, $C = 0.18pf$, $V = 12V$.

Total Power Consideration

Up to this point, we have completed the calculation process from CPU computational power to power consumption. However, a computer consists of more than just the CPU. Figure 3 illustrates the power consumption distribution of typical server components[5].

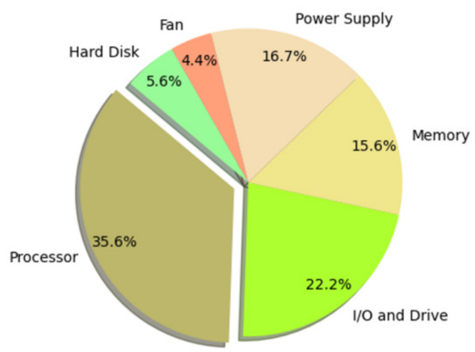

Fig. 4 Typical Server Components

Based on this, some further analyses have been done. First, we need to know the power consumption percentage of the CPU. From the chart in Fig. 4, the CPU power consumption is approximately 32%. Then, we can use this percentage to calculate the total power consumption of the server. Assuming the single-core CPU power consumption is *P64CPU*, the total power consumption of the server can be calculated using the following formula:

$$P_{64total} = \frac{P_{64CPU}}{0.32} \quad (16)$$

3.4 The Total Number of 64-core CPU Cores Required

Given the required computing power, we can determine the number of CPU cores needed:

$$n(t) = \frac{f(t)}{F} \quad (17)$$

$n(t)$ represents the number of 64-core CPU cores required in year t, $f(t)$ represents the total computing power demand in year t, and F represents the computing power demand for a 64-core CPU.

3.5 The Carbon Footprint of Total Computing Power

From Equations (16) and (17), given the global demand for computing power, we can understand that the power consumption of all CPUs is:

$$P_{total} = n(t) \times P_{64total} \quad (18)$$

The energy consumed over a certain period is:

$$E = P_{total} \times T \quad (19)$$

Finally, we build the relationship between energy consumption and carbon emissions:

$$C_{CO_2} = \lambda \times E \times L \quad (20)$$

where: L is the load factor, meaning E refers to the energy consumption under full power conditions, and L is the average percentage of the computer's capacity used (100% for full load operation, 50% for average utilization). λ is the CO_2 emission factor, λ = 0.5 kg/(kW·h). (According to the "Research on CO_2 Emission Factors of China's Regional Power Grids 2023" released by the Environmental Planning Institute of the Ministry of Ecology and Environment.)

4 Considering renewable energy

The integration of renewable energy sources has notably impacted the value of traditional energy sectors, and according to the electricity generation statistics released by the National Bureau of Statistics for 2020, thermal power generation, primarily from coal-fired plants, reached 5.28 trillion kilowatt-hours (kWh), constituting 71.19% of the nation's total electricity production. That indicates that coal-based power generation still represents nearly three-quarters of the overall mix. However, projections suggest that by 2030, the thermal power generation market share will decrease to about one-third. Consequently, the yearly percentage of thermal power generation is expected to shift significantly over this period. Therefore, the annual proportion of thermal power generation is:

$$\frac{5}{12} \times \frac{(2030 - year)}{(2030 - 2020)} + \frac{4}{12}$$

In this scenario, λ is:

$$\lambda \times \left(\frac{5}{12} \times \frac{(2030 - year)}{(2030 - 2020)} + \frac{4}{12} \right)$$

The energy structure changes significantly as the world transitions towards a low-carbon economy. By 2030, the proportion of renewable energy is expected to increase substantially, while fossil fuels will gradually decrease. This shift will directly impact the carbon emissions from HPC facilities.

Different energy types have varying carbon emission factors, which reflect the amount of CO_2 emitted per unit of energy produced. Below are the carbon emission factors for several major energy types (in grams of CO_2 per kilowatt-hour):

Table 4 Carbon Emissions for Various Energy Sources

Energy Source	Carbon Emissions (gCO_2/kWh)
Coal	949
Natural Gas	469

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Energy Source	Carbon Emissions (gCO_2/kWh)
Oil	749
Wind	11
Solar	48
Nuclear	12

To more accurately assess the carbon emissions from HPC, it is necessary to incorporate changes in the energy mix and the carbon emission factors of different energy types. The specific steps are as follows:

(a) Determine the Energy Mix Proportions:

Assume the proportions of renewable energy and fossil fuels each year are $r_{re}(t)$ and $r_{ff}(t)$, respectively, where:

$$r_{re}(t)+r_{ff}(t)=1$$

(b) Calculate Total Energy Consumption:

Calculate Energy Consumption for Each Type:

Renewable Energy Consumption:

$$E_{re}(t)=E(t)\times r_{re}(t)$$

Fossil Fuel Consumption:

$$E_f f(t)=E(t)\times r_{ff}(t)$$

(c) Calculate Carbon Emissions:

Renewable Energy Carbon Emissions:

$$C_{re}(t)=E_{re}(t)\times f_{re}$$

Fossil Fuel Carbon Emissions:

$$C_f f(t)=E_{ff}(t)\times f_{ff}$$

Total Carbon Emissions:

$$C(t)=C_r e(t)+C_f f(t)$$

f_{re} and f_{ff} are the carbon emission factors for renewable and fossil fuels.

5 Solution of the Model

5.1 Carbon Emissions in 2023

The global computational demand prediction is:

$$f(t)=2.1382\times exp(0.2763\times 23)=1230.12EFLOPS$$

According to Equation (15), the power consumption of a 64-core CPU is:

$$\mathrm{P_{64cpu}}=\mathrm{C_0}+C\cdot \mathrm{V}^2\cdot\left(\frac{\mathrm{F}}{\mathrm{a\times e}}\right)=0.001+0.18pf\times 12^2\times\frac{2648.064\mathrm{TFLOPS}}{64\times 16}=6.703\times 10^{-2}\mathrm{W}$$

According to Equation (17), the required number of CPU cores is obtained as follows:

$$n(2023)=\frac{f(2023)}{F}=\frac{1230.12EFLOPS}{2648.064TFLOPS}=4.646\times 10^6$$

Then, According to Equation (28), the total power consumption of all CPUs is:

$$P_{total}=n(2030)\times P_{64total}=4.646\times 10^6\times 6.703\times 10^{-2}=311.421KW$$

Based on the CPU's 32% power consumption, the total power consumption is:

$$P_{total}=\frac{P_{CPU}}{0.32}=\frac{311.421KW}{0.32}=973.192KW$$

The HPC energy consumption for the year 2023 is:

$$E=P_{total}\times T=973.192\times 24\times 365=8525160.278kWh$$

Full Load Operation:

$$C=\lambda\times E\times L=0.5\times\frac{9}{12}\times 8525160.278\times 100\%=3196.935t$$

Average Operation:

$$C=\lambda\times E\times L=0.5\times\frac{9}{12}\times 8525160.278\times 5096=1598.468t$$

Based on the constructed model's estimates, in 2023, the annual carbon emissions from HPC at full load will be approximately 3196.935 tons, while the average yearly carbon emissions during operation will be approximately 1598.468 tons.

5.2 Prediction for the Year 2030

The global computational demand prediction is as follows:

$$f(t) = 2.1382 \times exp(0.2763 \times 30) = 8509.72\text{EFLOPS}$$

According to Equation (15), the power consumption of a 64-core CPU is:

$$\text{P}_{\text{64cpu}} = \text{C}_0 + C \cdot \text{V}^2 \cdot \left(\frac{\text{F}}{\text{a} \times \text{e}}\right) = 0.001 + 0.18\,pf \times 12^2 \times \frac{2648.064\text{TFLOPS}}{64 \times 16} = 6.703 \times 10^{-2}\,\text{W}$$

According to Equation (17), the required number of CPU cores is obtained as follows:

$$n(2030) = \frac{f(2030)}{F} = \frac{8509.72EFLOPS}{2648.064TFLOPS} = 3.214 \times 10^7$$

Then, According to Equation (28), the total power consumption of all CPUs is:

$$P_{total} = n(2030) \times P_{64total} = 3.214 \times 10^7 \times 6.703 \times 10^{-2} = 2490.85\text{KW}$$

Based on the CPU's 32% power consumption, the total power consumption is:

$$P_{total} = \frac{P_{CPU}}{0.32} = \frac{2490.85KW}{0.32} = 7783.9\text{KW}$$

The HPC energy consumption for the year 2030 is:

$$E = P_{total} \times T = 7783.9 \times 24 \times 365 = 68187018.75\text{kWh}$$

Full Load Operation:

$$C = \lambda \times E \times L = 0.5 \times \frac{1}{3} \times 68187018.75 \times 100\% = 11364.503t$$

Average Operation:

$$C = \lambda \times E \times L = 0.5 \times \frac{1}{3} \times 68187018.75 \times 50\% = 5682.251t$$

Based on the constructed model's estimates, in 2030, the yearly carbon emissions from HPC at full load will be approximately 11364.503 tons, while the average annual carbon emissions during operation will be approximately 5682.251 tons.

5.3 Providing Reasonable Upper and Lower Estimates

5.3.1 Optimistic Estimate

Assuming the proportion of renewable energy increases to 80%, and the proportion of fossil fuels decreases to 20%:
Full Load Operation:

$$C = \lambda \times E \times L = 0.5 \times \frac{2}{10} \times 68187018.75 \times 100\% = 6818.702t$$

Average Operation:

$$C = \lambda \times E \times L = 0.5 \times \frac{2}{10} \times 68187018.75 \times 50\% = 3409.351t$$

5.3.2 Pessimistic Estimate

Assuming the proportion of renewable energy remains at 20%, and the proportion of fossil fuels is at 80%:
Full Load Operation:

$$C = \lambda \times E \times L = 0.5 \times \frac{8}{10} \times 68187018.75 \times 10096 = 27274.807t$$

Average Operation:

$$C = \lambda \times E \times L = 0.5 \times \frac{8}{10} \times 68187018.75 \times 50\% = 13637.404t$$

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6 Extended Model

6.1 Water Usage

Power Usage Effectiveness (PUE) is an essential indicator for evaluating the low-carbon green performance of HPC platforms. It is defined as:

$$PUE = \frac{TotalEnergyConsumption}{ComputerEnergyConsumption} \tag{21}$$

“Total Energy Consumption” includes the energy used by computers, cooling systems, power supply systems, lighting, auxiliary devices, etc.

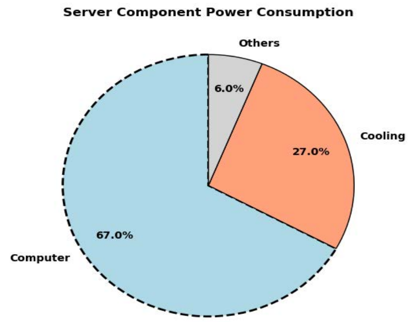

Fig. 5 The Energy Consumption Ratio of the HPC (PUE = 1.5)

As illustrated in Figure 4, The energy consumption of computer and cooling systems accounts for more than ninety percent of the total energy consumption of HPC platforms. A lower PUE value indicates that most of the energy is consumed by servers, network devices, storage devices, and other ICT equipment, signifying a higher degree of platform greening.

We use a PUE of 1.5 as an example, adopting the $P_{total} = 7783.9KW$ calculated as the computer energy consumption, resulting in the energy consumption of the cooling system being:

$$P_{cooling} = \frac{ComputerEnergyConsumption}{0.67} \times 0.27 = \frac{7783.9}{0.67} \times 0.27 = 3136.8KW$$

Then, the energy consumption of the cooling system is:

$$E_{cooling} = P_{cooling} \times T = 3136.8 \times 24 \times 365 = 27714888KWh = 9.97735968 \times 10^{13} J$$

The water temperature for the computer cooling system typically ranges from 18℃ to 27℃ for the inlet water (water entering the cooling system) and from 25℃ to 30°C for the outlet water (water exiting the cooling system). We take the inlet water temperature as 18℃ and the outlet water temperature as 30℃ to maximize the utilization of the cooling water. According to the specific heat capacity formula:

$$Q = m \cdot c \cdot \Delta T \tag{22}$$

Q is the heat energy transferred (in joules, J), m is the mass of the substance (in kilograms, kg), c is the specific heat capacity of the substance (in joules per kilogram per degree Celsius, 4186 J/ (kg·°C)), ΔT is the change in temperature (in degrees Celsius).

The mass of cooling water is:

$$m = \frac{Q}{c \cdot \Delta T} = \frac{9.97735968 \times 10^{13} J}{4186 \times (30 - 18)} = 1.986 \times 10^{9} kg$$

The mass of cooling water is:

$$V = \frac{m}{\rho} = \frac{1.986 \times 10^{9} kg}{1000kg / m^{3}} = 1.986 \times 10^{6} m^{3}$$

6.2 Electronic Waste

The overall electronic waste can be represented as:

$$G_{waste} = U_{years} \times k_{sum} \times p \times W_{computer} \tag{23}$$

Gwaste is the weight unit of electronic waste in tons, *Uyears* is the service life of the e-computing cluster, *p* is the scrap rate, *Wcomputer* is the weight of electronic waste in one computer unit, and the sum and sum is the total number of computers. In more detail, the quantity of hardware units is influenced by the size of the data center and the frequency of hardware upgrades. Assuming that 10% of the hardware is replaced each year:

$$k_{sum} = \left(1 + p_{new}\right)^{years} \times k_{sum_{init}} \tag{24}$$

where *ksum* is the total number of computers, Ipsum is the annual growth rate, years are the difference between the calculation year and the initial year, and $k_{sum_{init}}$ is the initial total number of computers.

6.3 Exhaustion of Resources

The depletion of resources can be represented as:

$$N_{loss} = k_{sum} \times (n_{smelt} + n_{resources}) \qquad (25)$$

The loss of a calculation unit can be decomposed into two parts: 1. fuel consumption used in the production and smelting process, and 2. resource consumption composed of the product. The unit product smelting and resource consumption is represented by *nsmelt* and coefficient *nresources*.

More specifically, suppose the total number of hardware units in a data center is 10000 by 2030. Assuming that the resource consumption of each hardware unit is 0.0003 tons of rare earth materials and 0.002 tons of coal are consumed for smelting, the total energy consumption is:

$$\mathrm{N_{loss}} = \mathrm{k_{sum}} \times (\mathrm{n_{smelt}} + \mathrm{n_{resources}}) = (0.0003 + 0.002) \times 10000 = 23(\mathrm{tons})$$

6.4 Land Use

The land use can be expressed as:

$$A_{land} = N_{datacenters} \times A_{unit} \qquad (26)$$

where, *Aland* is the total land use area (in square meters), *Ndatacenters* is the number of data centers (in units), and *Aunit* is the land use area per data center (in square meters per unit). In more detail, the number of data centers: Let's assume there are 1,000 large-scale data centers globally in 2030.The land use area per data center: Let's assume that each data center occupies an area of 10,000 square meters. The total land-use area is calculated as:

$$A_{land} = N_{datacenters} \times A_{unit} = 1,000 units \times 10000 squaremeters / unit = 10,000,000 squaremeters$$

6.5 Air Quality

The air quality substance usage can be expressed as:

$$P_{emissions} = E_{HPC} \times C_{emissions} \qquad (27)$$

where, *Pemissions* is the total air pollutant emissions (in tons), *EHPC* is the annual energy consumption of HPC (in kWh), and *Cemissions* is the air pollutant emissions per kWh (in tons per kWh). For further clarification, let's assume that each kWh of electricity consumption generates 0.001 tons of air pollutants:

$$C_{\mathrm{emissions}} = 0.001 \ \text{tons/kWh}$$

6.6 Chemical Substance

The total chemical substance usage can be expressed as:

$$C_{total} = V_{cooling} \times C_{unit} \qquad (28)$$

where, C_{total} is the total amount of chemical usage, $V_{cooling}$ is the capacity of the cooling system, and C_{unit} is the number of chemicals per liter of coolant.

Capacity of the cooling system: Let's assume that the cooling system of each data center has a capacity of 1,000,000 liters:

$$V_{\mathrm{cooling}} = 1,000,000 \text{liters}$$

Amount of chemicals per liter of coolant: Let's assume that each liter of coolant contains 0.1 liters of chemicals:

$$C_{unit} = 0.1 \ \text{liters/liter}$$

The total amount of chemical usage is calculated as follows:

$$C_{total} = V_{cooling} \times C_{umit} = 1,000,000 \ \text{liters} \times 0.1 \ \text{liters/liter} = 100,000 \ \text{liters}$$

7 Practical Tips to Reduce HPC's Environmental Impact

7.1 Technical Solutions

(a) Enhancing Energy Efficiency: Advanced cooling methods, such as liquid cooling and phase-change cooling, can reduce the overall energy consumption of HPC systems, thereby reducing carbon emissions.

(b) Boosting Renewable Energy Usage: Promote the adoption of solar, wind, and other renewable energy sources to reduce dependence on fossil fuels and increase energy sustainability.

(c) Optimize data center location: Locate data centers in cooler areas to utilize natural cooling and reduce cooling costs. That minimizes the energy required for cooling, thereby reducing carbon emissions.

(d) Promote green supply chain practices: Use environmentally friendly materials and production processes to reduce resource use and pollution in the production process.

(e) Improve e-waste management: Develop e-waste recycling and proper disposal systems to increase recycling and reuse rates and enhance resource recycling.

7.2 Policy Solutions

(a) Setting stringent energy efficiency standards: Government agencies should set energy efficiency standards to incentivize technological innovation and improve energy efficiency across the sector.

(b) Financial incentives: Governments should provide tax breaks, subsidies, and other financial incentives to

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encourage businesses and research institutions to adopt energy-efficient technologies and renewable energy. That will reduce the cost of adopting environmentally friendly technologies and promote their wider application.
(c) Strengthen international cooperation: Promote global assessment and governance of HPC's environmental impacts through international organizations and multilateral agreements. Reach an international consensus to address HPC's environmental challenges jointly.
(d) Raise public awareness: Carry out public education and awareness campaigns to inform society of the environmental impacts of high-performance computing and encourage active participation by all sectors of society.

8 Conclusion

This paper develops a model to determine the environmental impact of HPC energy consumption based on the annual energy consumption of global HPC capacity. The potential impact of different energy sources on carbon emissions is characterized by combining different proportions of new energy sources. The model predicts that the annual carbon emissions of the HPC cluster in 2030 will be around 15,114.010 tonnes. The model is also extended to consider the impact of the cooling water required for HPC and the generation of e-waste to better understand the environmental impact of HPC through a case study. The assumptions and limitations of the model are discussed in detail, and ways to improve the model are proposed. Finally, based on the model assessment results, recommendations are made for technical and policy measures to reduce the environmental impacts of HPC, contributing to the coordinated development of science and technology and the environment.

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