Team Control Number

**15145**

Problem Chosen

**B**

**2024**

**HiMCM**

**Summary Sheet**

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# The Promotion of Green and Sustainable High-Powered Computing


In recent years, the rapid growth of global demand for High-Powered Computing (HPC)—driven by advancements in artificial intelligence (AI), data science, and cryptocurrency mining—has made the environmental impact of these technologies an urgent concern. This study presents a series of models to analyze the global energy consumption and environmental effects associated with HPC systems.

Firstly, our team collected and organized all available global data on HPC to estimate its annual energy consumption. We found that the total capacity energy consumption reaches 26.28 TWh per year, while the average utilization-based energy consumption is approximately 18.40 TWh annually. We then assessed carbon emissions from the entire lifecycle of HPC equipment, including production and operation, using the **Life Cycle Assessment (LCA) model** and **Monte Carlo Simulations**. Our calculations indicate that annual emissions amount to approximately 816 million kg $CO_2$ e.

Over the past decade, the combined performance of the Top500 supercomputers has doubled roughly every 1.2 years, in line with Moore's Law. Recognizing that such exponential growth may not be sustainable indefinitely, we applied a standard **logistic function** to forecast HPC capacity growth. Our model predicts that HPC capacity could be approximately 3.6 times higher in 2030 than in 2023. Based on the current average energy consumption of 18.40 TWh and an estimated emission intensity of 0.5 kg $CO_2$ e/kWh in 2023, we project that emissions could increase by 22% to 94% by 2030, depending on different scenarios.

Additionally, we used an integral representation to simulate water resource demand for HPC cooling systems. In a baseline scenario where the energy mix includes 30% coal, 20% natural gas, 40% renewables (20% solar and 20% wind), and 10% nuclear power, the total water usage for cooling is 55.77 million cubic meters. In an ideal scenario of 100% renewable energy, water usage could be reduced by 64.3%.

In conclusion, this comprehensive study highlights the significant environmental impact of HPC systems. We provide several recommendations to address these concerns, including increasing energy efficiency of HPC systems, adopting renewable energy sources, optimizing cooling management, and urging the Advisory Board to include a dedicated section in the 2030 developmental goals. We advocate for sustainable practices in the deployment and operation of HPC systems to mitigate their environmental footprint.



**Keywords:** High-Powered Computing (HPC), Energy consumption, Carbon emission, Water usage.

# Content

# 1 Introduction

## 1.1 Background

In recent years, as global demand for high-powered computing (HPC) grows rapidly, driven by advancements in artificial intelligence (AI), data science, and cryptocurrency mining, the environmental impact of these technologies has become an urgent concern. HPC, which requires the use of massive data centers, cutting-edge hardware, and energy-intensive computational processes, is at the forefront of this issue. The exponential increase in data generation and processing demands has led to the construction of increasingly larger and more energy-hungry data centers, which in turn contribute significantly to global energy consumption and carbon emissions. In particular, industries such as AI and machine learning require substantial computing power for tasks like deep learning, natural language processing, and computer vision, resulting in higher electricity usage and cooling requirements[1]. Similarly, cryptocurrency mining, especially with the rise of energy-demanding consensus mechanisms like Proof of Work (PoW), has been widely criticized for its environmental consequences, particularly in regions where electricity is generated from non-renewable sources[2].

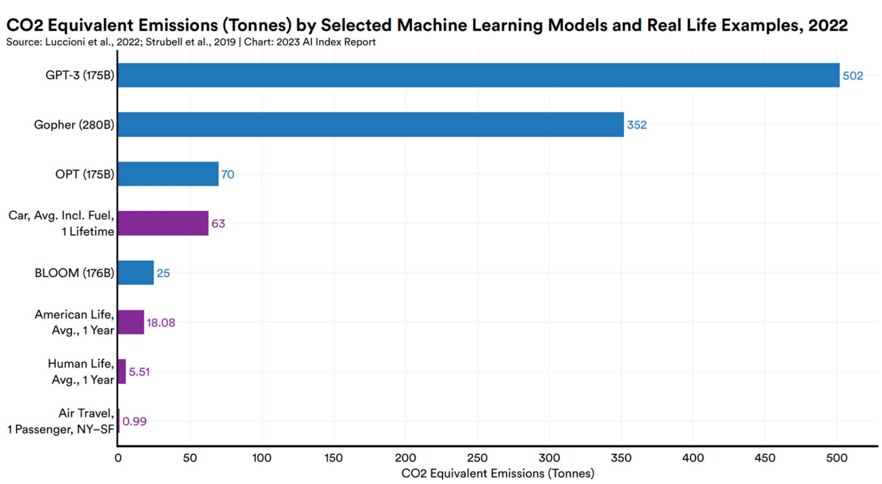


**Figure 1: $CO_2$ equivalent emissions for training ML models (blue) and of real-life cases (violet). In brackets, the billions of parameters adjusted for each model[3]**

When the HPC industry continues to expand, there is growing recognition of the need for sustainable practices to mitigate its environmental footprint. Researchers and industry leaders are exploring various solutions, such as energy-efficient hardware, renewable energy sources, and innovative cooling techniques, to reduce the environmental impact while maintaining computational performance. Furthermore, data centers are increasingly being designed with energy efficiency in mind, incorporating advanced cooling systems, server virtualization, and optimizing server workload management.

Furthermore, the environmental impact of HPC is primarily driven by energy consumption and the associated carbon emissions, which are significant contributors to climate change. Energy consumption directly correlates with greenhouse gas emissions, especially when electricity is sourced from fossil fuels. HPC facilities often require vast amounts of power, resulting in substantial carbon footprints. Moreover, the high energy demand can place a strain on local power grids, particularly in areas with limited renewable energy infrastructure, which exacerbates the reliance on non-renewable energy sources. Actually, HPC seems destined to play a dual role. On the one hand, it can help reduce the effects of the climate crisis, such as developing low-emission infrastructure, and modelling climate change predictions. On the other hand, HPC is itself a significant emitter of carbon. This message reached the attention of a general audience in the latter half of 2019 when researchers at the University of Massachusetts Amherst analyzed various natural language processing (NLP) training models available online to estimate the energy cost in kilowatts required to train them. Converting this energy consumption in approximate carbon emissions and electricity costs, the authors estimated that the carbon footprint of training a single big language model is equal to around 300,000 kg of carbon dioxide emissions. This is of the order of 125 round-trip flights between New York and Beijing, a quantification that laypersons can visualize[4].

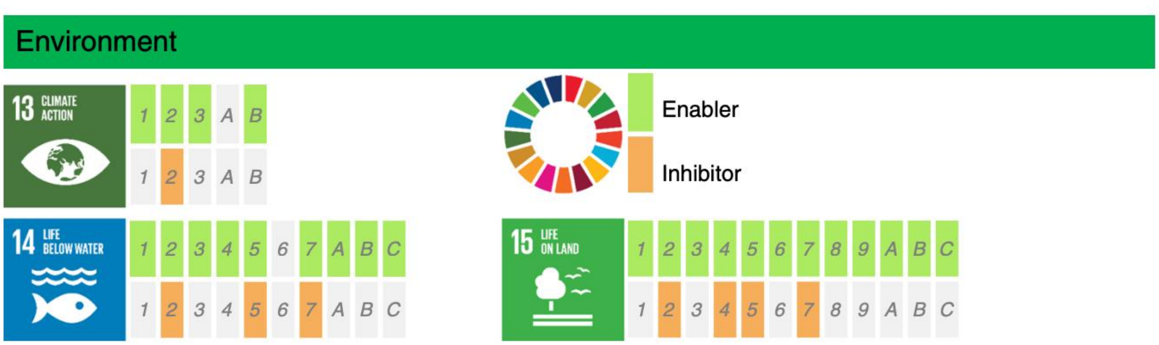

**Figure 2: Detailed assessment of the impact of AI on the SDGs within the Environment group [4],[5]**

Beyond energy consumption, several other environmental concerns arise from the operation of HPC systems. These concerns are multifaceted and can be categorized into the following key areas: water usage, E-waste, resource depletion, land use, air quality, chemical use, socioeconomic impacts, noise pollution, and network architecture[6]. These environmental concerns highlight the need for sustainable practices in the HPC industry to reduce its overall impact on the planet. At the same time, the pursuit of greener and more sustainable HPC solutions is critical in ensuring that the continued growth of AI, data science, and cryptocurrency mining does not come at the expense of the planet.

The rapid growth of HPC systems, such as artificial intelligence (AI), has raised concerns about their environmental impact. AI systems, particularly large-scale models, require substantial computational resources, resulting in significant energy consumption and carbon emissions. As AI becomes more pervasive across industries, understanding and mitigating its climate impact is increasingly critical.

A key issue in reducing AI's environmental footprint is the difficulty in quantifying its energy consumption and carbon emissions. Crawford and Joler (2020) argue that the material costs of large-scale AI systems are often vague, with many people perceiving AI development as a simpler task than it truly is. This misunderstanding arises partly because there is no standardized method for measuring the energy and emissions associated with AI systems. Without clear metrics, it is challenging to assess the true scale of AI's climate impact and implement effective mitigation strategies.[7]

## 1.2 Our work

Our work aims to analyze the global energy consumption of High-Power Computing (HPC) systems, considering both their full capacity and average utilization rates. We focus on estimating the total energy usage of HPC systems annually and the environmental impact this has. To assess the carbon emissions from this energy consumption, we developed a model that incorporates the energy production sources and mixes used to power HPC systems.

We then explored how our model might evolve in the future. This includes considering the growth of HPC, the increasing energy demand in other sectors, and shifts in energy sources.

Using the model, we estimated the potential environmental impact of HPC systems by 2030, providing insights into their future contribution to global carbon emissions.

In addition, we expanded our model to explore the impact of increasing the share of renewable energy in the energy mix. We calculated the potential reduction in carbon emissions with higher renewable energy usage and investigated the challenges of transitioning to 100% renewable energy sources. We also refined our model to include another key environmental factor related to HPC, which is closely tied to energy consumption, to gain a more comprehensive understanding of the issue.

Finally, based on our findings, we developed actionable recommendations to reduce the environmental impact of HPC. These recommendations include both technical solutions and policy-oriented approaches. We incorporated one of these recommendations into our model to demonstrate its potential effect on reducing emissions. In addition, we drafted a letter to the United Nations Advisory Board, urging them to include a more detailed section on the environmental impact of HPC in their 2030 goals, supported by our research and recommendations.

## 1.3 Model Overview

First, our team has collected and organized all available global data resources related to HPC, estimating the total global HPC capacity and average utilization. We analyze the global energy consumption of HPC systems based on standard energy consumption metrics.

Subsequently, we account for carbon emissions from the entire production and operational lifecycle of HPC equipment using the Life Cycle Assessment (LCA) model and Monte Carlo Simulations. We have developed a mathematical model to quantify the total carbon emissions resulting from HPC energy consumption, considering different energy mixes.

Next, considering that HPC capacity has been increasing exponentially, we construct a logistic function to predict the growth of HPC capacity and provide realistic bounds for the environmental impact problem projected for the year 2030.

Moreover, HPC data centers often require substantial water resources for their cooling systems. Water usage is directly linked to energy consumption through the cooling processes. However, high water consumption can strain local water supplies, impacting ecosystems and communities, such as agriculture. We use integral representation to simulate the demand for water resources needed for cooling systems.

Finally, based on our data and understanding of the issue, we will provide recommendations and write a letter to the United Nations Advisory Board to consider the environmental impacts of HPC.

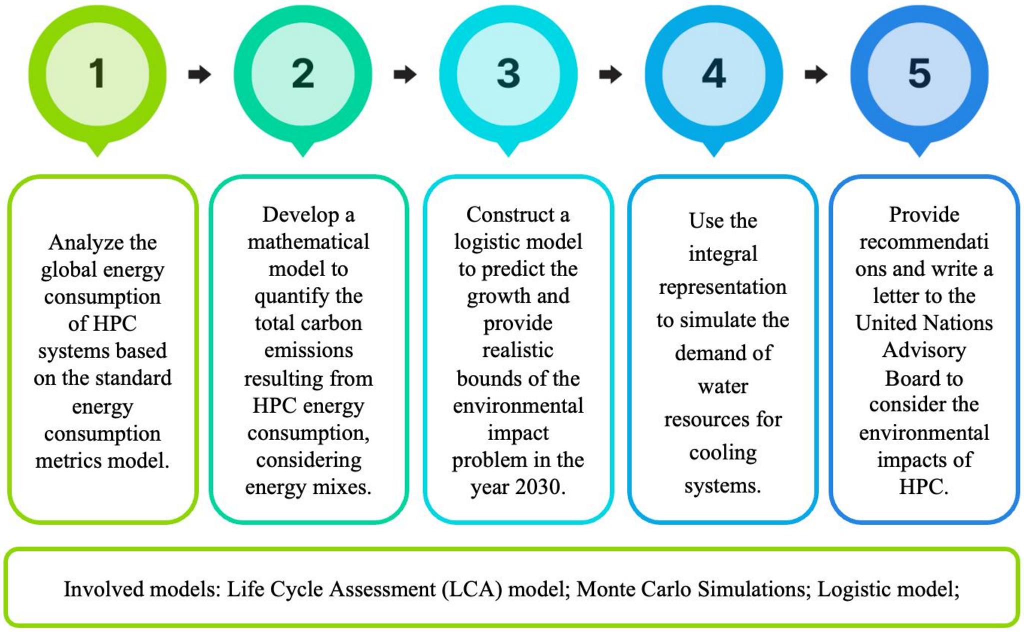


**Figure 3: Flowchart of this study**

# 2 Assumptions and Justifications

Several assumptions are listed to simplify the problem. The assumptions and their justifications are listed below:

**Assumptions 1:** Assuming that devices typically considered to require high computational power are all within the scope of HPC.

**Justifications 1:** HPC typically refers to the aggregation of powerful computing resources to execute complex computational tasks. It is defined as the use of supercomputers or clusters of computers to perform parallel processing, solving advanced problems in science, engineering, or data analysis at speeds much faster and with greater storage capabilities than traditional personal computers. However, since it is relatively unclear which devices fall under HPC, this study aims to clarify the scope of HPC as much as possible using available data.

**Assumptions 2:** Assume that the environmental impact of HPC in the model primarily include carbon dioxide emission and water usage.

**Justifications 2:** HPC operations typically require substantial electrical power, much of which is sourced from carbon-intensive energy production, thus contributing directly to greenhouse gas emissions. Additionally, the cooling systems necessary to maintain operational integrity of HPC facilities often demand considerable amounts of water, which places a strain on local water resources and impacts water sustainability. Therefore, these factors are critical in understanding and mitigating the overall environmental footprint of HPC systems.

# 3 Notations

Some important mathematical notations used in this paper are listed in Table 1.

**Table 1: Notations used in this paper.**

| Symbol | Description | Unit |
|---|---|---|
| $C_{total}$ | The combined computational power of all HPC systems worldwide. | PFLOPS |
| $U$ | The average percentage of time HPC systems are actively performing computations. | % |
| $P_{perPF}$ | The average power required to operate one petaflop of computational capacity. | kW |
| $T$ | The total number of hours in a year (for annual consumption). | hours |
| $E$ | Energy consumption. | $kWh$ |
| γ(t) | The effective carbon emission intensity at time *t*. | kg $CO_2$ e per kWh |
| $P_{idle}$ | The idle power consumption when the HPC system is not processing workloads. | kW |
| $P_{max}$ | The maximum power consumption at full computational load. | kW |
| $\phi_i(t)$ | The fraction of electricity generated from energy source i at time t. | —— |
| $W_{total}$ | The total water usage. | *liters* |

| | | |
|---|---|---|
| CCR | The estimated increase in global average temperature for every 1000 gigatons of $CO_2$ emitted. | 1000 Gt $CO_2$ |
| $\epsilon_i$ | The carbon emission factor for energy source i. | kg $CO_2e$/kWh |
| $\lambda$ | The conservative annual growth rate. | % |
| $\omega(t)$ | The water usage intensity at time t. | liters per kWh |

Note: There are some variables that are not listed here and will be discussed in detail in each section.

# 4 Models and Results

## 4.1 Energy Consumption Model (ECM)

### 4.1.1 Standard energy consumption metrics

For measuring power consumption, there are several methods, each with different outputs and characteristics. These measurement approaches can be broadly categorized into two types: out-of-band and in-band measurements. Out-of-band measurement, such as using external power meters, is often the simplest and most straightforward approach. It relies on external devices to measure power consumption without significantly interfering with the computational performance of the system. This method is particularly useful in situations where minimal disruption to system operations is desired[8]. In contrast, in-band measurement methods, such as RAPL (Running Average Power Limit) counters, require more technical knowledge about the target hardware. These methods can access specific registers and provide power consumption data programmatically, often in real-time. While in-band measurement is more integrated into the system and can offer more precise data, it typically requires a deeper understanding of the hardware and software interactions.

In order to express the energy consumption at any level, we use the most basic formula to link energy to power and time. The energy consumption $E$ can be expressed as:

$$E = \sum_{i=0}^{n} P_i T_i \tag{1}$$

where we assume a relatively constant power $P_i$ for time period $T_i$, with $T_0 + T_1 + \cdots + T_n = T$ , where $T$ is the overall time period considered. One might consider an average power $P$ of the $P_i$ over period $T$ and therefore write $E = P \times T$. With this basic formula, we can clearly see which are the two orthogonal levers at our disposal to act on energy consumption. The variations of $P$ and $T$ are quite opposite, indeed the energy optimization of an HPC system is a matter of a good trade-off between the execution time and the consumed power. The goal is to optimize one while keeping the other at an acceptable level.

The reference unit of energy measurement according to the international system of units is the Joule (*J*). In relation with a time period, there is the watt-per-hour or watt-hour (*Wh*), with the relation 1 *Wh* = $3.6 \times 10^3$ *J*. In this study we will use both of them, but in most of the cases we will refer to the Watt, which is reference unit of power (i.e. energy consumed in a time period of 1 hour).

The first approach to get the energy consumption of a given application is to directly measure the electrical power of the targeted hardware through specific devices (out-of-band approach). The second approach is to seek an approximation of energy consumption using a prediction/estimation model (usually considered for performance). The first method is often used to assess the accuracy of estimation approaches. Therefore, we use the first method to calculate the energy consumption.

According to the top500 ranking from June 2019 to June 2024[9], we obtained the calculated power consumption data of the top500 HCPS in the world (**Figure 4**).

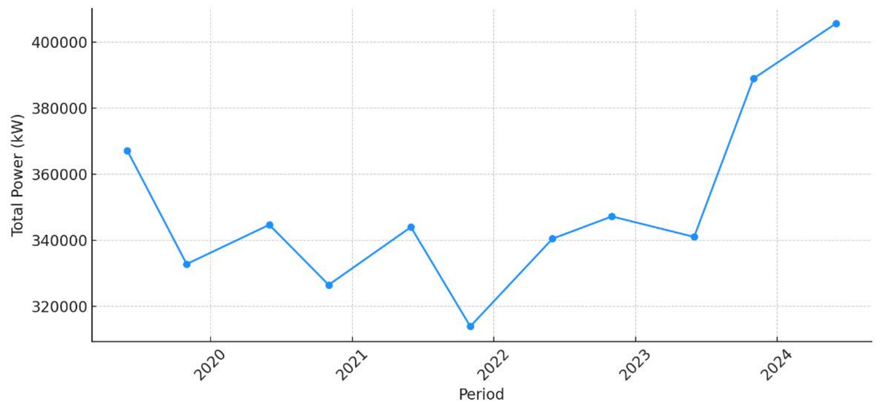


**Figure 4 Total power consumption for top 500 HPC**

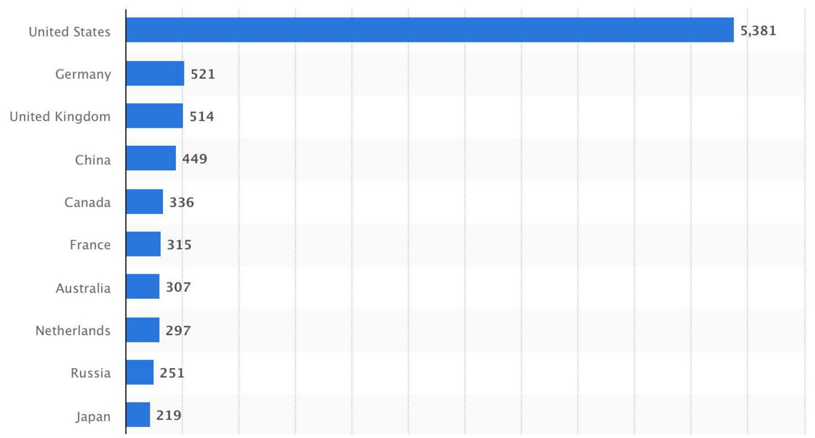


**Figure 5 Leading countries by number of data centers as of March 2024**

### 4.1.2 Model Solving

HPC systems are essential for advanced computational tasks across various industries. However, their significant energy consumption contributes to environmental concerns, particularly carbon emissions. To address this issue, we need a scientific model to estimate the annual energy consumption of HPC capabilities worldwide, considering both full capacity and average utilization rates.

Apart from energy consumption $E$, we introduced these parameters:

- Total Installed HPC Capacity $C_{total}$: The combined computational power of all HPC systems worldwide, measured in petaflops (PFLOPS).

- Average Power Consumption per Petaflop $P_{perPF}$ : The average power required to operate one petaflop of computational capacity, measured in kilowatts (kW).
- Utilization Rate $U$ : The average percentage of time HPC systems are actively performing computations.
- Total Operational Time $T$ : The total number of hours in a year (for annual consumption), which is 8760 hours/years.

The Top500 list (June 2024) reports that the combined performance of the top 500 supercomputers is approximately 5 exaflops (5000 PFLOPS). However, the Top500 list doesn't include all HPC systems worldwide (Table 1). To account for additional systems (research institutions, private companies, government agencies), we estimate the total global HPC capacity to be approximately 15000 PFLOPS.

Additionally, according to the **Fugaku Supercomputer** (442 PFLOPS with a power consumption of 29.9 MW) and **Summit Supercomputer** (148.6 PFLOPS with a power consumption of 13 MW), the Average Power Consumption per Petaflop $P_{perPF}$ are from 67.6 kW/PFLOP to 87.5 kW/PFLOP. Considering a range of systems, including less efficient ones, we estimate an average of 200 kW per PFLOP.

### (1) Full Capacity Energy Consumption

If HPC systems operate at full capacity continuously throughout the year ($U$ =100%), the annual energy consumption ($E_{full}$) is calculated as:

$$E_{full} = C_{total} \times P_{perPF} \times T \tag{1}$$

$$E_{full} = 15000\, PELOPS \times \frac{200kW}{PFLOP} \times 8760h = 26.28\, TWh \tag{2}$$

Therefore, the full capacity annual energy consumption is 26.28 TWh.

### (2) Average Utilization Energy Consumption

On average, the utilization rate of large-scale HPC systems can range from **50% to 70%** of their full capacity, meaning they are not constantly running at full load. This can result in energy consumption that is significantly lower than when the system operates at full capacity. A 70% utilization rate is an industry estimate; actual rates may differ based on workload and scheduling. In this study, we choose the 70% as the average utilization rate.

$$E_{full} = E_{full} \times U = 26.28\,TWh \times 0.7 = 18.396\,TWh \tag{1}$$

Therefore, the average utilization annual energy consumption is 18.40 TWh.

**4.1.3 Model Validation**

Furthermore, we compare the results from this model with the published data from global data center energy consumption. According to the International Energy Agency (IEA) in 2022, global data centers consume approximately 200–250 TWh annually. Our estimated HPC consumption of 18.40 TWh represents about 7.4% of the lower end of total data center energy consumption, which relatively aligns with the earlier estimate that HPC accounts for 10% of data center energy use. In particular, at present, there is no authoritative detailed data to support the complete calculation, so the results of this study can also provide an effective reference.

In conclusion, we estimate that the annual energy consumption of HPC capabilities worldwide is approximately 18.40 TWh at average utilization rates and could reach 26.28 TWh at full capacity. This significant energy consumption underscores the environmental impact of HPC systems and highlights the need for energy-efficient technologies and renewable energy integration.

## 4.2 Carbon Emissions Model (CEM)

High-Power Computing (HPC) systems are pivotal in advancing scientific research, artificial intelligence, and data analytics. However, their substantial energy consumption raises concerns about environmental sustainability, particularly regarding carbon emissions. To address these concerns, we need to develop a comprehensive mathematical model that quantifies the total carbon emissions resulting from HPC energy consumption, considering the energy production methods and regional energy mixes.

### 4.2.1 Model Analysis

Create a mathematical model to calculate the total carbon emissions ($E_{ctotal}$) associated with the energy consumption of HPC systems, accounting for: the energy consumption patterns of HPC systems, the energy mix (proportions of different energy sources) in various regions and the carbon emission factors of different energy sources.

The total carbon emissions can be expressed as:

$$E_{ctotal} = \int_0^T P(t) \cdot \gamma(t) dt \tag{1}$$

Where $E_{ctotal}$ is total carbon emissions over time period T (in tonnes $CO_2$ e), $P(t)$ is the power consumption of HPC systems at time t (in kilowatts), γ(t) is the effective carbon emission intensity at time t (in kg $CO_2$ e per kWh), and T is the total time period under consideration (e.g., one year). The power consumption $P(t)$ can be modeled as:

$$P(t) = P_{idle} + (P_{max} - P_{idle}) \cdot U(t) \tag{2}$$

Where $P_{idle}$ is the idle power consumption when the HPC system is not processing workloads, $P_{max}$ is the maximum power consumption at full computational load, and $U(t)$ is the utilization rate at time t (ranging from 0 to 1).

The effective carbon emission intensity depends on the energy mix used to supply electricity at time t:

$$\gamma(t) = \sum_i \phi_i(t) \cdot \epsilon_i \tag{3}$$

Where $\phi_i(t)$ means the fraction of electricity generated from energy source i at time t, and $\epsilon_i$ means carbon emission factor for energy source *i*. Additionally, the sum of all $\phi_i(t)$ must equal 1 at any time t.

Furthermore, since HPC facilities are distributed globally, and energy mixes vary by region, we extend the model to account for multiple regions. Let R be the set of regions where HPC facilities are located. The total carbon emissions become:

$$E_{ctotal} = \sum_{r \in R} \int_0^T P_r(t) \cdot \gamma_r(t) dt \tag{4}$$

To account for uncertainties in energy production, demand, and technological advancements, we introduce stochastic variables. Model parameters like $U_r(t)$ and $\phi_{i,r}(t)$ are treated as random processes. And we use **Monte Carlo Simulations** to simulate a wide range of scenarios and assess the probability distribution of total emissions.

Additionally, we incorporate the **Life Cycle Assessment (LCA)**. Beyond operational emissions, we include embodied emissions from manufacturing, transportation, and installation of HPC hardware and end-of-life emissions from decommissioning and recycling equipment.

$$E_{ctotal} = E_{operational} + E_{embodied} + E_{end-of-life} \tag{5}$$

Therefore, the model can be described as,

$$E_{ctotal} = \sum_{r \in R} \int_0^T [P_{idle,r} + (P_{max,r} - P_{idle,r}) \cdot U_r(t)] \cdot \gamma_r(t) dt + E_{embodied} + E_{end-of-life} \tag{6}$$

### 4.2.2 Model Solving

Based on the above model establishment and analysis, we selected the data of two regions for analysis and solution. The situation of the two regions is shown in the **Table 2**.

**Table 2 The parameters for two distinct regions.**

| Parameters | Region A | Region B |
|---|---|---|
| $P_{idle}$ | 5 MW | 3 MW |
| $P_{max}$ | 10 MW | 6 MW |
| $U(t)$ | 0.8 | 0.6 |

| | | |
|---|---|---|
| Energy mixes | 30% coal, 20% natural gas, and 50% wind | 40% natural gas and 60% solar |

According to the IPCC Emission Factor Database, the emission factors for coal is 1.0 kg $CO_2$e/kWh, natural gas is 0.5 kg $CO_2$e/kWh, wind is 0.011 kg $CO_2$e/kWh and solar is 0.048 kg $CO_2$e/kWh.

Therefore, we calculate that region A will produce 31,978,620 kg $CO_2$e and Region B 9,627,302 kg $CO_2$e during operation. approximately 41,606 tonnes $CO_2$e was produced.

Typical values of embodied emissions range from 500 to 1,200 kg $CO_2$ e per kW of IT equipment and end-of-life emissions factor is generally less than 5% of the embodied emissions. Therefore, we use 800 kg $CO_2$ e per kW of IT equipment and calculate that region A will produce 2,212,608,000 kg CO2e for embodied emissions, 110,630,400 kg CO2e for end-of-life and Region B 1,475,072,000 CO2e for embodied emissions, 73,753,600 kg CO2e for end-of-life.

In summary, Region A produces annualized embodied and end-of-life emissions of approximately 464,647,680 kg $CO_2$ e per year, and operational emissions of about 31,978,620 kg $CO_2$ e per year, leading to total annual emissions of 496,626,300 kg $CO_2$ e per year. Similarly, Region B has annualized embodied and end-of-life emissions of approximately 309,765,120 kg $CO_2$ e per year and operational emissions of about 9,627,302 kg $CO_2$ e per year, resulting in total annual emissions of 319,392,422 kg $CO_2$ e per year. Combined, the total annual emissions for both regions amount to approximately 816,018,722 kg $CO_2$ e per year.

### 4.2.3 Model Interpretation

Based on previous calculations, Regions A and B collectively emit approximately 816,018,722 kg of $CO_2$ equivalent per year (about 816,019 tons of $CO_2$ e). Assuming there are 100 similar regions worldwide, the total emissions would amount to 81.6 million tons of $CO_2$ e. According to the Global Carbon Project[10], global $CO_2$ emissions in 2020 were around 3.415 billion tons of $CO_2$ e. This suggests that the HPC systems in Regions A and B alone would contribute approximately 0.24% of the annual global carbon emissions. To assess the impact of these carbon emissions on global temperatures, we can use the concept of Carbon Climate Response (CCR). CCR represents the estimated increase in global average temperature for every 1000 gigatons of $CO_2$ emitted. According to the IPCC Fifth Assessment Report, the estimated CCR value is around 1.0°C per 1000 Gt $CO_2$.

$$\Delta T = CCR \times \frac{E_{total}}{1000} Gt\ CO_2 = 8.16 \times 10^{-5} ℃ \tag{1}$$

The annual carbon emissions from Regions A and B lead to a global average temperature increase of approximately 0.0000816°C. While this figure has a limited impact when considered in isolation, carbon emissions have a cumulative effect. Assuming that the HPC systems continue to operate at the same emission levels over the next 10 years, the cumulative carbon emissions would result in a global average temperature increase of about **0.000816°C**.

In addition to carbon emissions, the operation of HPC systems involves significant water consumption, particularly in the cooling process. According to data from the U.S. Department of Energy[11], each kWh of energy consumption requires 1.8 liters of water for cooling. This means that annual water consumption would reach **3.3 billion cubic meters**. High levels of water use in a single region can place stress on local water supplies, especially in areas facing water scarcity, impacting agricultural, industrial, and residential water usage.

## 4.3 Towards 2030 Calculation

HPC capacity has been increasing exponentially. Over the past decade, the combined performance of the Top500 supercomputers has roughly doubled every 1.2 years, following Moore's Law. Exploring how the comprehensive model developed earlier may change in the future with the growth of HPC, increasing energy demand in other sectors, and potential shifts in energy sources and mixes is important. Therefore, we construct a model to provide realistic bounds that offer insight into the scope of the environmental impact problem in the year 2030.

Considering that exponential growth may not be sustainable indefinitely, we can use **logistic function** to predict the growth of HPC capacity.

$$C_{total}(t) = \frac{K}{1 + e^{-r(t-t_0)}} \tag{1}$$

Assuming a conservative annual growth rate of 20% ($\lambda = \ln(1.2) \approx 0.182$), HPC capacity could be approximately **3.6 times** higher in 2030 than in 2023.

As HPC capacity grows, energy consumption would increase proportionally if energy efficiency remains constant. In reality, the advances in processor technology, cooling systems, and algorithms could improve energy efficiency. We assume an annual improvement in energy efficiency of 10%. So, power consumption per PFLOP could be reduced by approximately **52.2%** by 2030. Utilization can increase from **70%** to **80%** due to higher demand for computational resources.

However, there are increased electricity demand due to the shift from internal combustion engines to electric vehicles (EVs), growing population and economic development. Higher electricity demand may challenge the expansion of renewable energy sources.

Therefore, we set three scenarios:

- **Ideal Scenario:** Renewables make up **100%** or more of the global energy mix.
- **Optimistic Scenario:** Renewables make up **50%** or more of the global energy mix.
- **Moderate Scenario:** Renewables account for **30–40%**.
- **Pessimistic Scenario:** Slow growth leads to only **20–25%** renewables.

### 4.3.1 Model Establishment & Solving

According to the parameters calculated before, we can update the model:

$$C_{total}(2030) = 3.6 \times C_{total}(2023) = 54000\, PFLOPS \tag{1}$$

$$P_{perPF}(2030) = 0.478 \times P_{perPF}(2023) = 95.6\, kW/PFLOP \tag{2}$$

And the full capacity energy consumption in 2030 can be

$$E_{full}(2030) = C_{total}(2030) \times P_{perPF}(2023) \times T \times U(2023) = 36.21\, TWh \tag{3}$$

Therefore, through calculations, we determine that the cost of one electric bus is 1,339,196 yuan, and the cost to be borne by internal funds is 669,584.5 yuan.

**Table 3 Future energy mix scenarios.**

| Energy mix | Ideal scenario | Optimistic scenario | Moderate scenario | Pessimistic scenario |
|---|---|---|---|---|
| Renewables | 100% | 50% | 35% | 25% |
| Fossil fuels | 0 | 40% | 55% | 65% |
| Nuclear and others | 0 | 10% | 10% | 10% |

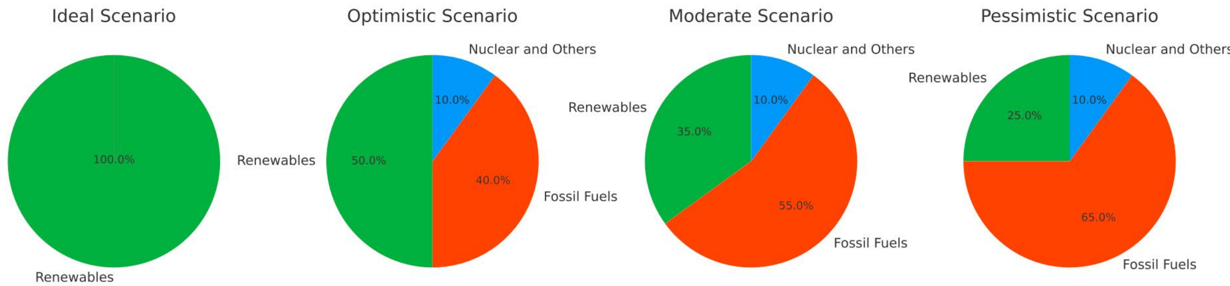


**Figure 6 The different energy mix scenarios.**

According to the IPCC Emission Factor Database, the emission factors for renewables (average) is 0.02 kg $CO_2$e/kWh, and for nuclear is 0.012 kg $CO_2$e/kWh.

Calculating effective carbon emission intensity, we can get the $\gamma_{ide} = 0.02\,kg\,\frac{CO_2e}{kWh}$, $\gamma_{opt} = 0.3112\,kg\,\frac{CO_2e}{kWh}$, $\gamma_{mod} = 0.4207\,kg\,\frac{CO_2e}{kWh}$, $\gamma_{pes} = 0.4937\,kg\,\frac{CO_2e}{kWh}$.

Therefore, in the ideal scenario, the total $CO_2$ emission is approximately 0.7242 million tonnes annually; in the lower bound (optimistic scenario), the total $CO_2$ emission is approximately 11.27 million tonnes annually; in the upper bound (pessimistic scenario), the total $CO_2$ emission is approximately 17.88 million tonnes annually; and in the moderate estimate, the total $CO_2$ emission is approximately 15.24 million tonnes annually.

Using the earlier average energy consumption of 18.40 TWh and an average emission intensity (assuming 0.5 kg $CO_2$e/kWh) in 2023, we can estimate that the emissions could increase by **22% to 94%** depending on the scenario by 2030 (without the consideration of ideal scenario). In the ideal scenario, as shown, switching to 100% renewables reduces operational carbon emissions by **over 95%**.

#### 4.3.2 Model Interpretation

In terms of the results above, it is illustrated that despite improvements in energy efficiency, the rapid growth in HPC capacity may lead to a substantial increase in total carbon emissions. While HPC's share of global emissions remains relatively small, the trend reflects broader challenges in balancing technological advancement with environmental sustainability. In particular, the proportion of renewable energy in the electricity mix significantly affects total emissions and aggressive policies promoting renewable energy adoption can mitigate the environmental impact of HPC growth.

### 4.4 Water Usage Model

HPC data centers often require substantial water resources for cooling systems. Water usage is directly linked to energy consumption through cooling processes. However, high water consumption can stress local water supplies, affecting ecosystems and communities like agriculture.

#### 4.4.1 Model Establishment & Solving

We introduce the $\omega$ as the water usage intensity at time t (liters per KWh), which may vary due to cooling efficiency changes. The total water usage $W_{total}$ can be modeled as:

$$W_{total} = \int_0^T P(t) \cdot \omega(t) dt \tag{1}$$

The cooling systems can be divided into three ways, including evaporative cooling, chilled water systems and air cooling. We assume the water usage varies significantly across energy sources: coal: 1.9 liters/kWh; natural gas: 1.0 liters/kWh; nuclear: 2.5 liters/kWh; solar PV: 0.1 liters/kWh; wind: 0 liters/kWh (negligible); hydroelectric: high water use but non-consumptive (water remains in the system). We can calculate the weighted average $\omega_{power\_gen}$ based on the energy mix.

For the baseline example with 30% coal, 20% natural gas, 40% renewables (20% solar and 20% wind) and 10% nuclear, the total water usage is

$$W_{total} = 55\ 769\ 400\ 000 \text{ liters} = 55{,}769{,}400 \text{ cubic meters} \tag{2}$$

As renewable energy increases, the water usage for power generation changes due to lower water intensity of renewables. When considering the 100% renewables in an ideal scenario, we can reduce 64.3% water usage.

### 4.4.2 Model Interpretation

HPC facilities located in arid or drought-prone areas can intensify existing water scarcity issues due to their huge water usage, which may compete with local demands for agriculture, drinking water, and ecosystem maintenance. Additionally, the discharge of heated water from these facilities can contribute to thermal pollution, raising temperatures in nearby water bodies and potentially affecting aquatic life. The use of chemicals in cooling systems also poses risks to water quality; water treatment chemicals may contaminate local water sources if not properly handled, and cooling towers that are not adequately maintained pose a risk of harboring Legionella bacteria, which can be harmful to health.

## 5 Sensitivity Analysis

Sensitivity analysis is a crucial step in model evaluation and interpretation as it provides insights into how variations in model inputs impact the model outputs. By examining how changes in input values affect the model results, sensitivity analysis aids in quantifying the model. In summary, sensitivity analysis enhances the transparency and credibility of mathematical models by shedding light on the relationships between input parameters and model outputs.

Therefore, we conducted a sensitivity analysis on the parameters of the Carbon Emission Model. Using published energy structure data from specific regions, we performed the analysis and found that, based on the current common energy mix, the total annual carbon emissions from HPC systems remain relatively stable. This demonstrates the robustness of the model.

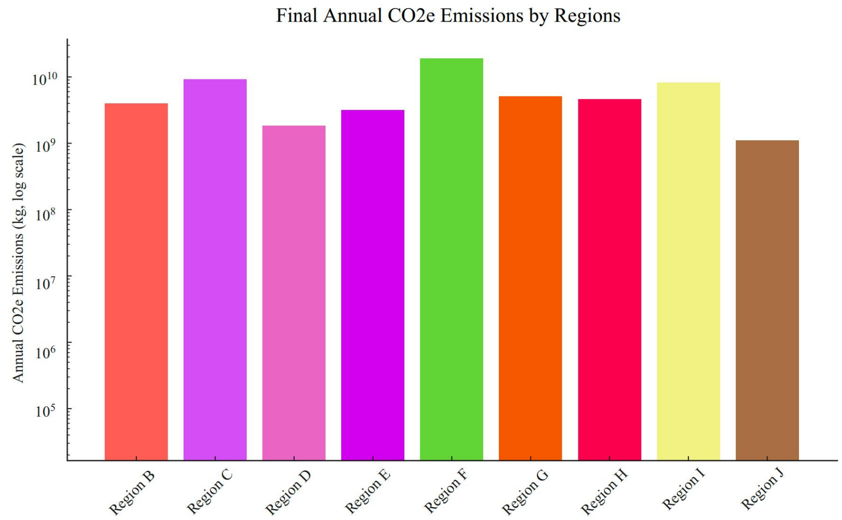


**Figure 7 The sensitive analysis of carbon emission model.**

# 6 Evaluation of Strengths and Weaknesses

This model provides comprehensive consideration of both carbon emissions and financial aspects related to buses. The analysis is accurate, and the solution process of the model is intuitive and easy to understand. It helps people better understand the significance of the widespread adoption of electric buses in real-life situations.

However, there is still room for improvement in this model. For instance, due to limited data availability, the simulation of current HPC energy consumption may be inaccurate. In addition, the model does not account for the noise pollution generated by HPC systems.

# Letter

**Subject:** Green Computing 2030: Integrating Environmental Impact Assessments of High-Performance Computing into Developmental Goals

Dear Members of the United Nations Advisory Board,

I am writing to propose a critical oversight in the report, *"Governing AI for Humanity."* While the report offers valuable insights into the governance of AI, it does not significantly address the environmental impacts associated with High-Performance Computing (HPC), which underpins much of AI's advancement. As we approach 2030, the growth of HPC capabilities is accelerating, driven by the increasing demands of AI, data analytic, and scientific research. Our recent studies have shown that if left unchecked, the environmental footprint of HPC could become a substantial contributor to global carbon emissions and resource depletion.

**The Important Findings：(1) Projected Growth:** HPC capacity is expected to increase by approximately 3.6 times by 2030 compared to 2023 levels. **(2) Energy Consumption:** Without intervention, annual energy consumption by HPC systems could reach over 36 TWh by 2030. **(3) Carbon Emissions:** Depending on the energy mix, carbon emissions from HPC could rise to between 11 to 18 million tonnes of $CO_2$ equivalent annually. **(4) Water Usage:** HPC operations could consume significant volumes of water for cooling and power generation, exacerbating water scarcity in vulnerable regions.

To mitigate these environmental impacts, we have developed a set of actionable recommendations:

1. **Increase Energy Efficiency of HPC Systems**
   - Invest in energy-efficient hardware and software solutions.
   - Encourage the development of algorithms that optimize computational efficiency.
2. **Adopt Renewable Energy Sources**
   - Transition HPC facilities to renewable energy through on-site generation or renewable energy contracts.
   - Support the integration of energy storage systems to manage variability.
3. **Optimize Cooling and Resource Management**
   - Utilize advanced cooling technologies that reduce water and energy usage.
   - Implement circular economy practices for hardware lifecycle management.

By acting on these recommendations, we can significantly reduce the environmental impact of HPC, such as reducing carbon emissions by up to 45%, cutting water usage by over 60%. These measures support Sustainable Development Goals (SDGs) 7 (Affordable and Clean Energy), 9 (Industry, Innovation, and Infrastructure), and 13 (Climate Action), promoting environmental sustainability.

The rapid expansion of HPC technologies necessitates immediate attention to their environmental consequences. As leaders in global governance, the United Nations has the unique capacity to influence policies and foster international collaboration. Therefore, we urge the Advisory Board to include a comprehensive section on the environmental impacts of HPC in the upcoming developmental goals for 2030 and advocate for sustainable practices in the deployment and operation of HPC systems.

Thank you for considering this important matter. I am available to discuss these findings further and to support the integration of sustainable practices into global policies.

Sincerely,
All members in this team

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# Appendix

**Appendix 1**

Introduce: ***Growth of capacity for HPC systems ; Matlab***

```
% Parameters
K = 3.6; % Upper limit of the HPC capacity relative increase by 2030
t0 = 2023; % Starting year
t_end = 2030; % End year for projection
r = log(1.2); % Growth rate (20% annual growth)

% Time vector
t = t0:t_end; % Year range from 2023 to 2030

% Logistic function calculation
C_total = K ./ (1 + exp(-r * (t - t0)));

% Plotting
figure;
plot(t, C_total, '-o');
xlabel('Year');
ylabel('HPC Capacity (relative increase)');
title('Projected Growth of HPC Capacity');
grid on;
```

# AI Use Report

We used ChatGPT to help us retrieve information on the global development and relevant data of High-Performance Computing (HPC). However, due to the possibility of errors in ChatGPT's responses, we manually verified each retrieval result before applying it to this study.

Prompts:

Can you help me to collect the data related the High-Performance Computing (HPC) systems globally, and summarize the important information about this?

Please describe the development of HPC systems.

Please search the top HPC devices and introduce them.