Team Control Number

15022

Problem Chosen

B

2024
HiMCM
Summary Sheet

SUMMARY SHEET

High-Powered Computing (HPC) is essential for scientific research, technology development, and data analysis. As organizations use HPC for complex tasks like climate modeling, molecular simulations, AI, and big data analytics, significant energy consumption, primarily from fossil fuels, and the resulting carbon emissions have become a major global concern.

As the problem mentioned, other than carbon emission, many ecosystem-related concerns are associated with the utilization and construction of HPC facilities. However, according to the UN's Advisory Board on AI (2024), environmental impacts from training AI models via HPC make up a minor part of AI-related issues. Nonetheless, the ecological effects of HPC energy consumption remain significant. This paper will use mathematical modeling to explore the global environmental and economic impacts of rising HPC facility usage.

The first requirement involved analyzing the annual energy consumption of HPC capabilities globally, considering both full capacity and average utilization rates. To address this, our team examined a decade's worth of data on HPC energy consumption and developed a function linking increased computing power to rising energy demands. We discovered that as HPC computing power grows, its escalating energy requirements are a significant concern.

The second requirement was to develop a comprehensive model to assess the environmental impact of carbon emissions from HPC energy consumption, considering different energy mixes. To address this problem, we created a Multi-factor Dynamic Prediction Model for HPC Carbon Emissions. By dividing the energy consumed into two main parts—fossil fuel and renewable energy, we quantified the carbon emissions from HPC energy consumption and constructed the simple function used for rough prediction.

In the third requirement, we were asked to improve and apply our model. After considering the impact of various factors on the model, including the growth of HPC, the increasing demand for energy in other sectors, and the potential for different energy sources and mixes, our model became more precise. According to our prediction, by the year 2030, the total carbon emission of HPCs will rise to 2342483383.33 tCO2, taking up 5.21% of global total emissions.

The fourth requirement was to refine our model to include an additional environmental factor and the increasing proportion of renewable energy. To take the growth of the proportion of renewable energy into account, we added some additional variables to our model and considered the use of cooling water as an additional environmental impact.

Finally, we recommended some actionable improvements to reduce the environmental impact of HPCs and included one in our model to show the results of the improvements.

Contents

1. Introduction

1.1. Background

The rapid advancement of high-performance computing (HPC) has spurred unprecedented growth in sectors such as artificial intelligence (AI), data science, and cryptocurrency mining. This surge in computational demand has led to the widespread development of HPC facilities and massive data centers, which provide the necessary infrastructure for handling large-scale computations at high speeds. However, this increase in computational capability comes with significant environmental costs. Among these, energy consumption stands out as one of the most pressing concerns, as it directly correlates with greenhouse gas emissions and other environmental impacts. The energy-intensive nature of HPC facilities places substantial pressure on power grids, often requiring vast quantities of electricity, much of which is generated from fossil fuels. This dependency results in a substantial carbon footprint, which contributes to climate change and poses challenges for regions with limited renewable energy options. Beyond energy consumption, HPC facilities impact the environment in several other ways, including substantial water usage for cooling, the generation of electronic waste, resource depletion due to the extraction of rare materials, and localized land use that can affect ecosystems and communities. Given the growing role of HPC in global industries and its associated environmental impacts, it is critical to develop a comprehensive model that can quantify and project these effects.

1.2. Problem Restatement

The model developed in this study aims to address the core environmental issues posed by the rising energy demands of high-performance computing (HPC) and its associated carbon footprint. Below is a precise restatement of the primary questions, each specifying a key objective within the model:

Annual Energy Consumption of Global HPC : To assess the global annual energy consumption of HPC facilities by evaluating both the maximum (full-capacity) energy usage and the actual energy used based on average utilization rates. This analysis will quantify the energy demands of HPC systems and establish a baseline for assessing their environmental impact.

Constructing a Carbon Emission Model : To develop a model that quantifies the carbon emissions resulting from HPC energy consumption. This model must account for the varying sources of energy (e.g., fossil fuels, renewables) and allow for the estimation of carbon output based on different energy mixes. The flexibility of this model to accommodate diverse energy sources is essential for evaluating potential scenarios for emissions reduction.

Future Growth of HPC Demand and Environmental Impact : To project HPC energy demands through 2030 and analyze the associated environmental impacts. This task includes estimating how increased energy needs in other sectors and potential changes in energy sources will influence future HPC-related emissions and overall environmental footprint.

Impact of Increasing Renewable Energy Share on Carbon Emissions : To integrate a rising share of renewable energy into the model and calculate the corresponding reductions in carbon emissions. This involves investigating scenarios where renewable energy fully replaces non-renewables and assessing the feasibility and challenges of transitioning to a 100% renewable energy infrastructure for HPC.

Expanding the Model to Include Additional Environmental Factors : To expand the model to address other environmental impacts of HPC, such as water usage, e-waste, and resource depletion, allowing for a more comprehensive understanding of HPC's environmental effects. The chosen additional factor should demonstrate relevance to both energy consumption and broader ecological and societal impacts.

2. Assumptions

Assumption 1 : It is assumed that the annual energy consumption of HPC is primarily composed of the energy consumption of global data centers dedicated to HPC tasks and the energy consumption of cryptocurrency mining. Since AI computations rely on the infrastructure of data centers, the energy consumption attributed to AI usage is not additionally included in the statistics.

Assumption 2 : The energy consumption of data centers can be divided into three categories: traditional, cloud(non-hyper scale), and hyper-scale. We assume that hyperscale is associated with HPC tasks.

Assumption 3 : Given that global HPC facilities are primarily concentrated in the United States, China, Japan, Germany, France, the United Kingdom, Italy, Switzerland, Russia, India, South Korea, Brazil, Canada, Australia, Saudi Arabia, Spain, the Netherlands, Sweden, Norway, and Finland, we assume, for computational simplicity, that the total HPC energy consumption in these countries is equivalent to the global total for HPC energy consumption.

Assumption 4 : The energy consumption structure of HPC facilities is difficult to quantify. To simplify the model, we assume that the energy structure of HPC facilities mirrors the energy mix of the region or country in which they are located, recognizing that energy structures vary across regions and countries. Unless otherwise specified, we do not account for the emergence of alternative energy sources or the depletion of specific energy types.

Assumption 5 : It is assumed that each country's energy mix consists of three main components: fossil fuels, renewable energy, and nuclear power. Fossil fuels include coal, coke, oil, and natural gas, while renewable energy encompasses hydropower, wind, and solar energy.

Assumption 6 : Based on relevant data, it is assumed that by 2090, the proportion of renewable energy in countries with HPC facilities will approximate 100%. Given that nuclear energy development relies on the extraction of rare minerals, we anticipate that renewable energy will gradually replace nuclear energy in the future.

Assumption 7 : When discussing the functional relationship between global HPC carbon emissions and time, we use the proportion of renewable energy to represent the impact of the energy mix on carbon emissions. This approach is justified by the relatively stable proportion of nuclear energy across countries.

3. Notations

Symbol	Definition
E_{HPC}	Annual energy consumption of the HPC
E_{DC}	Annual energy consumption of data centers
E_{Crypto}	Annual energy consumption of cryptocurrency mining
P	Global computing power
C	Carbon emissions from global HPC energy consumption
C_i	Carbon emissions from HPC energy consumption in country i
x_i	Energy consumption of HPC in country i
r	HPC growth rate
ρ	The proportion of renewable energy
θ	The competition coefficient from other industries for energy
I	The environmental impact of global carbon emissions
W_t	Impact on the environment from Water usage
W_e	Impact on the environment from E-Waste

4. Requirement 1 : HPC Annual Energy Consumption Model

4.1. Model establishment

HPC is utilized for AI, data science, and cryptocurrency mining, relying primarily on infrastructure like data centers. Given the difficulty in directly quantifying global HPC energy consumption, we estimate it indirectly by equating the energy consumption of data centers used for HPC tasks plus that of cryptocurrency mining to the global HPC energy footprint. This relationship can be described as follows:

$$E_{\text{HPC}} = E_{\text{Crypto}} + k \cdot E_{\text{DC}} \tag{1}$$

Here, k represents the proportion of total global data center energy consumption associated with HPC tasks.

4.1.1. *Quantifying the proportion of total global data center energy consumption associated with HPC tasks*

As shown in Fig.1 and 2, the data is sourced from the IEA (International Energy Agency) [1] and the Cambridge Centre for Alternative Finance [2].

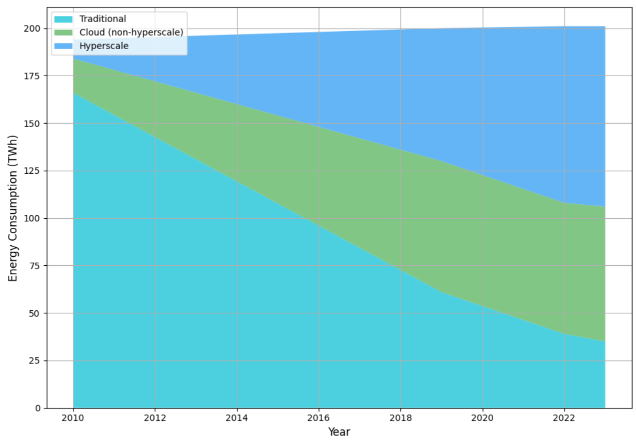

Figure 1: The proportion of total global data center energy consumption associated with HPC tasks k from 2010 to 2023.

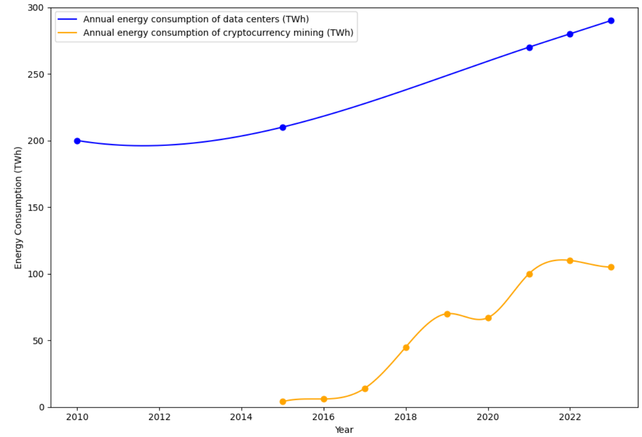

Figure 2: Annual energy consumption of data centers E_{DC} and Annual energy consumption of cryptocurrency mining E_{Crypto} from 2010 to 2023.

From Fig.1 and 2, we observe the proportion of total global data center energy consumption related to HPC tasks from 2010 to 2023, alongside the annual energy consumption of data centers and cryptocurrency mining. Based on Equation (1), the annual HPC energy consumption from 2010 to 2023 can be calculated by summing the yearly data, as shown in Fig.3. Based on data provided by global computing power statistical agency [3], the trend of global computing power over time is shown in Fig.4.

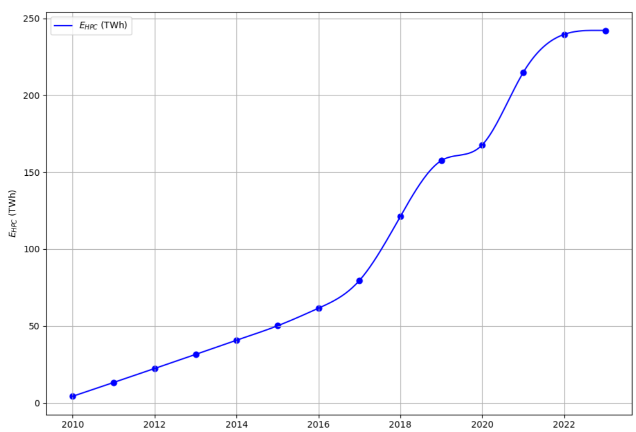

Figure 3: Annual energy consumption of the HPC E_{HPC} from 2010 to 2023.

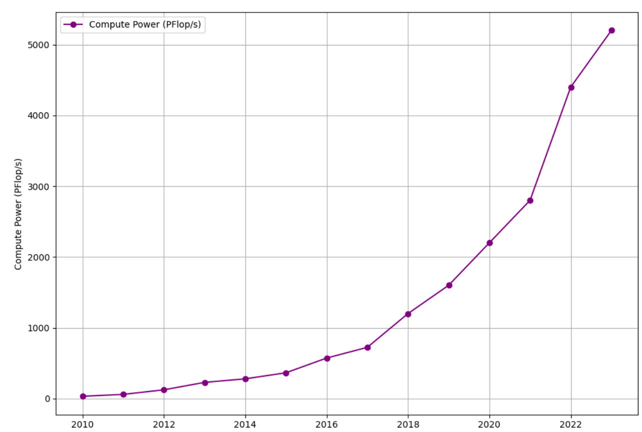

Figure 4: Annual global computing power P from 2010 to 2023.

4.1.2. *Quantifying the global HPC energy consumption and function fitting*

According to relevant literature[4], the relationship between HPC energy consumption and global computing power is characterized by the following correlation.

$$E'_{HPC} = a \cdot \ln (u \cdot P) + b \tag{2}$$

Here, a and b are parameters to be fitted from the data, and u represents the utilization rate, reflecting the average utilization rate of global HPC infrastructure.

Due to the rapid growth in global computing power after 2018, we have entered an era of computing power saturation. Consequently, the utilization rate u has decreased compared to the pre-2018 period. Based on available data[5], we set the utilization rate at 60% before 2018 and 50% thereafter. Using the data from Fig.3 and 4, along with the relationship between HPC energy consumption and global computing power described in Equation (2), we performed a function fitting analysis. The resulting function graph is shown in Fig.5.

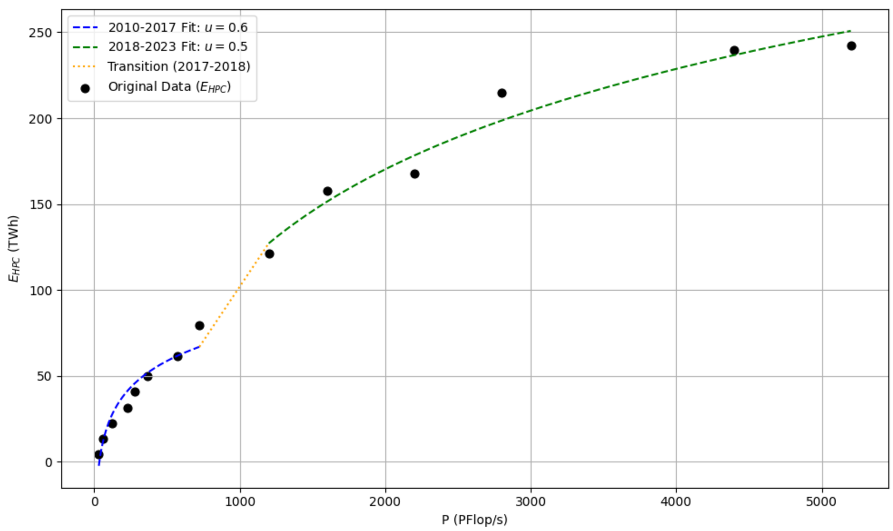

Figure 5: Fitted function graph of HPC energy consumption E_{HPC} and global computing power$P$.

The function fitting results are as follows:

$$\begin{cases} E_{HPC} = 22.29 \ln (0.6P) - 68.42 & 2010 \ll T < 2018 \\ E_{HPC} = 84.32 \ln (0.5P) - 412.23 & 2018 \ll T < 2024 \end{cases} \tag{3}$$

Using the HPC Annual Energy Consumption Model and Equation (3), with the global computing power in 2024 estimated at 8200 PFlop/s, the projected HPC energy consumption E_{HPC} for 2024 is 289.21 TWh. This aligns with the IEA's estimate in the World Energy Outlook 2024[6], which places global HPC energy consumption in the range of 240 to 340 TWh, thereby validating the accuracy and feasibility of the model.

4.2. Qualitative and quantitative analysis

With the increasing demand for high-performance computing (HPC) in AI, data science, and cryptocurrency mining, the annual energy consumption of HPC systems is drawing attention to its impact on global energy resources and carbon emissions.

From a qualitative analysis perspective, the rise in HPC system energy consumption not only reflects the accelerating global demand for computation but also reveals how varying energy structures and load patterns impact overall consumption. HPC systems and data centers have become significant components of energy use, with their share in total electricity demand steadily increasing. Additionally, cryptocurrency mining has intensified energy demand further, highlighting the distinctive energy consumption profile of this emerging sector and its pressure on global energy resources.

From a quantitative analysis perspective, the energy consumption of global HPC is related to global computing power by the following relationship: Meanwhile, according to the IEA[1], global data center energy consumption reached approximately 240-340 TWh in 2023, accounting for about 1%-1.3% of global electricity demand, excluding cryptocurrency mining. The Cambridge Centre for Alternative Finance reported that the Bitcoin network consumed 110 TWh in 2022, representing about 0.4% of global demand, which highlights the increasing energy impact of mining. HPC energy consumption depends on both the full-load power requirements and the average utilization rate. Due to the complexity and variability of HPC tasks, actual consumption is typically well below the theoretical maximum. Thus, an accurate assessment of HPC energy usage requires consideration of both full-load power needs and actual utilization rates.

5. Requirement 2 & 3 : Multi-factor Dynamic Prediction Model for HPC Carbon Emissions

5.1. Quantifying the carbon emissions from HPC energy consumption

To more accurately quantify the carbon emissions from HPC energy consumption, we consider the energy consumption and energy mix of HPC facilities in different countries or regions and establish the following model:

$$C = \sum C_i = \sum x_1 \cdot \alpha_i x_i + c_2 \cdot \beta_i x_i + c_3 \cdot \gamma_i x_i \tag{4}$$

Here, c_1 is the average carbon emission factor for fossil fuels, c_2 is the average carbon emission factor for renewable energy, and c_3 is the carbon emission factor for nuclear energy. These factors quantify the impact of each energy type on total carbon emissions. The variables α_i, β_i, and γ_i represent the proportions of fossil fuels, renewable energy, and nuclear energy in the energy mix of country i, respectively, and they satisfy the condition $\alpha_i + \beta_i + \gamma_i = 1$.

Based on data provided in the literature[3], we can obtain the total computing power for each country from 2010 to 2023, as shown in Fig.6.

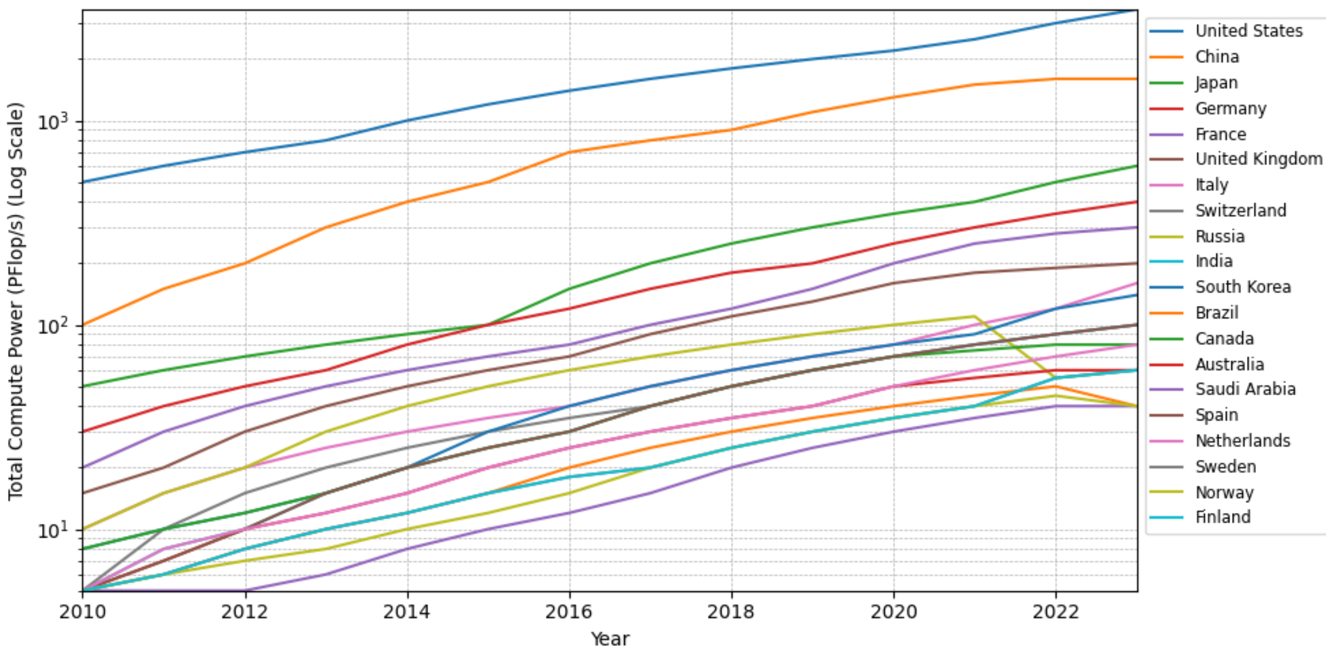

Figure 6: Total computing power of each country P from 2010 to 2023.

Combining this with the data from Fig.5, we can estimate each country's total HPC energy consumption E_{HPC} from 2010 to 2023, as illustrated in Fig.7.

To reduce computational complexity, we focus on the average carbon emission factors for different types of energy. For the carbon emission factor c_1 of fossil fuels, we use reported values for coal, oil, and natural gas at $820gCO_2/kWh$, $650gCO_2/kWh$, and $450gCO_2/kWh$, respectively[7]. We define the fossil fuel carbon emission factor as $c_1 = 0.4\times820+0.3\times650+0.3\times450 = 658gCO_2/kWh = 658000tCO_2/TWh$. Similarly, the carbon emission factor for renewable energy is $c_2 = 26000tCO_2/TWh$, and for nuclear energy, $c_3 = 12000tCO_2/TWh$. It is worth noting that the lower carbon emission factor for nuclear energy primarily reflects emissions associated with fuel extraction and facility construction stages.

According to data from the U.S. Energy Information Administration, we obtained the energy mix of countries including the United States, China, Japan, Germany, and France from 2010 to 2023. Selected data are shown in Table 1.

Country	**Year**	**Fossil Fuels (%)**	**Renewable Energy (%)**	**Nuclear (%)**
United States	2010	83.0	8.0	9.0
United States	2023	70.0	21.0	9.0
China	2010	90.0	8.0	2.0
China	2023	83.5	14.5	2.0

Table 1: Energy Structure of the United States and China in 2010 and 2023

Based on Equation (4), Fig.7, and the energy mix of each country from 2010 to 2023, we can calculate

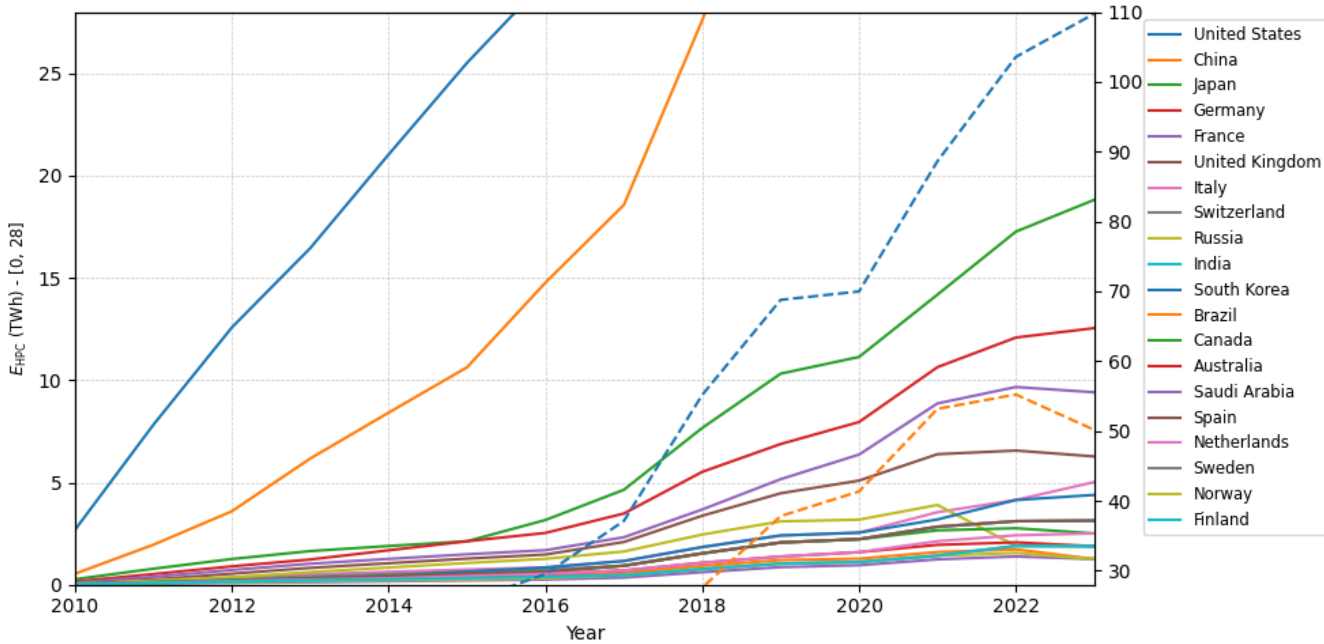

Figure 7: Energy consumption of HPC in each country E_{HPC} from 2010 to 2023.

the total global carbon emissions from HPC for the same period, as shown in Fig.8.

In summary, we obtained a graph showing the change in total HPC carbon emissions over time. Next, we need to construct a new function to describe this relationship, taking into account several critical influencing factors. The purpose of quantifying the carbon emissions from HPC energy consumption is to determine the optimal parameter values for this function, allowing the model to accurately predict future global HPC carbon emissions.

5.2. Constructing a function for global HPC carbon emissions over time

To construct a function for global HPC carbon emissions over time, we need to consider the influence of multiple factors, such as the growth rate of HPC, changes in the proportion of renewable energy, and competition from other energy-intensive industries. Therefore, it is essential to individually examine the relationship between each factor and time to identify the parameters that are variable and those that remain constant.

5.2.1. *Exploring the relationship between the HPC growth rate r and time t*

Assuming a global HPC growth rate of r, relevant literature[8] indicates that this growth rate remains relatively stable, with an almost constant annual rate. Therefore, to quantify the global HPC growth rate r, we only need to analyze the relevant data[3]. The results of this analysis are shown in Fig.9.

Based on the data fitting results, we find that the global HPC growth rate r is 49.46%, which aligns with the range provided in the relevant literature. Due to the widespread adoption of artificial intelligence,

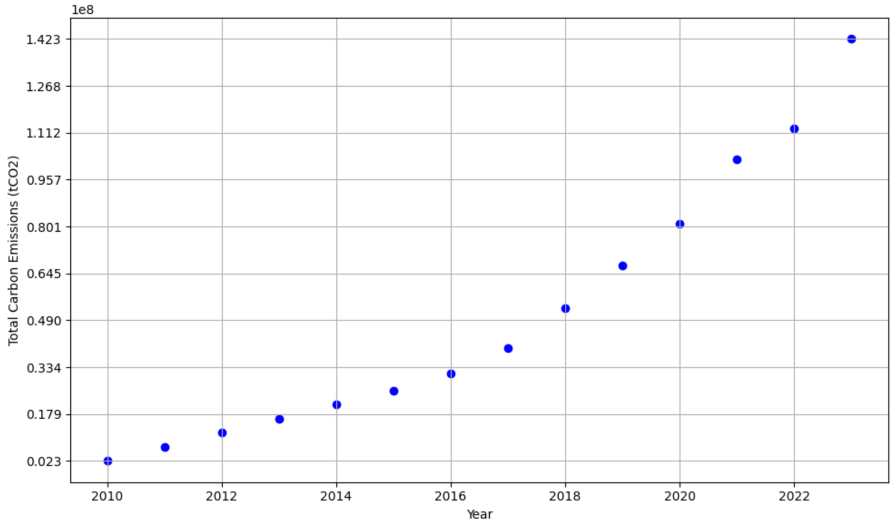

Figure 8: Total global HPC Carbon Emissions C from 2010 to 2023.

high-performance computing remains a strategic resource for many countries. Over the coming decades, the global HPC capacity is expected to continue growing at a rate of 49.46%. This relatively stable growth rate is primarily maintained because, although there is substantial national investment, further increases in computing power require breakthroughs and innovations in technology[9].

5.2.2. *Exploring the relationship between the proportion of renewable energy ρ and time t*

Based on the energy mix of each country from 2010 to 2023[7], we found that the proportion of nuclear energy within the mix of fossil fuels, renewable energy, and nuclear power has remained largely unchanged. This is due to the long construction timelines and high costs associated with nuclear infrastructure. In contrast, the proportions of fossil fuels and renewable energy have shown more significant changes over time. Additionally, since the carbon emission factor c_1 for fossil fuels and c_2 for renewable energy differ substantially, we focus primarily on the variation in the proportion of renewable energy rho in our analysis.

Based on Fig.10, which illustrates the relationship between the proportion of renewable energy ρ and time t, we can derive the following relationship: $\rho = \frac{0.9192 \cdot (t-2010)+26.45}{100}$.

5.2.3. *Constructing a Multi-factor dynamic prediction function for HPC carbon emissions*

In addition to considering the growth rate of HPC and the changes in the proportion of renewable energy, we also need to account for competition from other energy-intensive industries for energy resources. To quantify this competition, we introduce a factor θ. A larger value of θ indicates that HPC secures a greater share of energy in the competition. Since the competition from other industries is unpredictable and does not change over time, we assume, based on relevant literature[10], that $\theta = 1$, reflects the current state of energy surplus. Based on these premises and assumptions, we define the total global HPC carbon emissions over time t with the following equation (5):

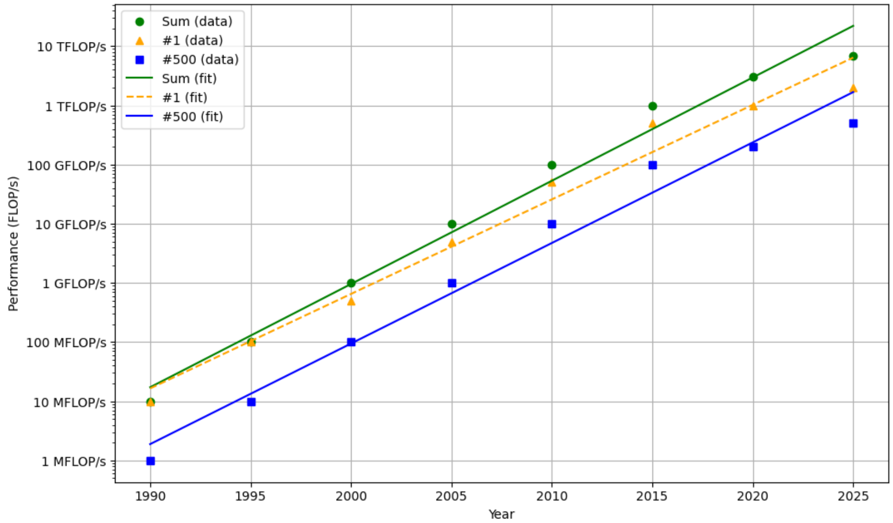

Figure 9: The relationship between the global HPC growth rate r and time t.

$$C_t = \theta[m \cdot (1+r)^{t-2010} + n \cdot (1-\rho) + s] \tag{5}$$

Here, m, n and s are parameters with no specific physical meaning. Based on the global HPC carbon emissions over time, as shown in Figure 8, we perform a curve fitting of Equation (5) to obtain the specific function for global HPC carbon emissions over time, C_t, as represented by Fig.11 and Equation (6).

$$C_t = \theta[750293.04(1+r)^{t-2010} + 6567.91(1 - (\frac{0.9192 \cdot (t-2010) + 26.45}{100})) + 21184010.47] \tag{6}$$

5.2.4. *Environmental impact of global HPC carbon emissions model*

According to relevant literature[11], the impact of global carbon emissions on the environment can be defined by the following equation:

$$I = \omega_1 \cdot (a \cdot lnC + b) + \sum g(\omega_i \cdot y_i) \tag{7}$$

Here, ω_i represents the weight of multiple factors generated by HPC that impact the environment, which may include water usage, e-waste, resource depletion, land use, chemical use, and so on. Also $\sum \omega_i = 1$ holds. y_i represents the various environmental impact factors generated by HPC.

Since the problem does not require considering other environmental factors, we set $\omega_1 = 1$. By combining the data from Fig.7, we can plot the following Fig.12.

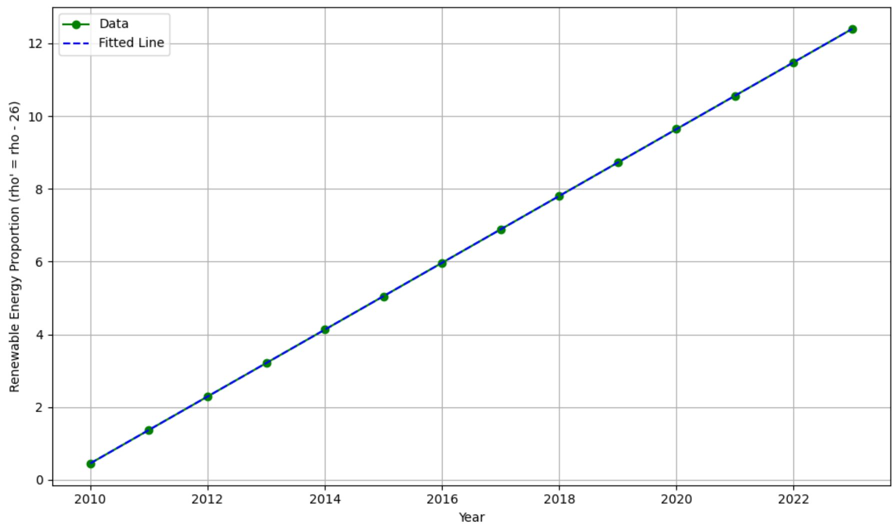

Figure 10: The relationship between the proportion of renewable energy rho and time t.

5.3. Model sensitivity analysis : Exploring the Impact of Various Factors on the Model

To investigate the impact of the growth of HPC, the increasing energy demand in other sectors, and the potential influence of different energy sources and mixes on the model, we will employ the method of controlling for variables to explore the effects of these factors.

5.3.1. *Exploring the impact of HPC growth on the model*

To explore the impact of HPC growth on the model, we can differentiate Equation (6) with respect to r, yielding the equation (8) :

$$\frac{\partial C}{\partial r} = \frac{750293.04(r+1)^{(t-2010)}(t-2010)}{(r+1)} \tag{8}$$

Clearly, the partial derivative of C with respect to r is greater than 0, meaning that as the growth rate of HPC increases, global HPC carbon emissions also increase. Through a review of the literature[12], we understand that the global HPC growth rate is expected to increase over time. However, by the middle of this century, the growth rate may peak and then begin to decrease as time progresses. This could be due to limitations in computing power development and the saturation of computing resources.

As shown in Fig.13, the blue line represents the original HPC carbon emissions over time, while the green line illustrates the change in HPC carbon emissions over time after a 40% change in the HPC growth rate post-2030. The red line shows the change in HPC carbon emissions over time after a 60% change in the HPC growth rate post-2030. It is evident that a sudden shift in the HPC growth rate does not lead to significant changes in carbon emissions in the short term. However, from a long-term perspective, carbon emissions will increase almost exponentially. A sudden decrease in the HPC growth rate may be due to

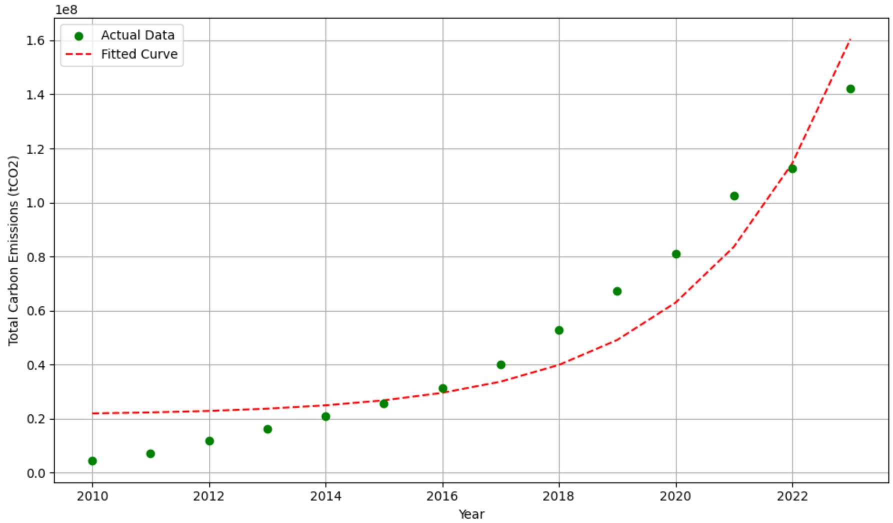

Figure 11: The relationship between carbon emissions from HPC energy consumption C and time t.

computing resource saturation or reduced demand, while an increase could be driven by technological breakthroughs or changes in national policies.

5.3.2. *Exploring the impact of competition from other industries for energy on the model*

To investigate the impact of competition from other industries for energy on the model, the partial derivative of Equation (6) with respect to θ is calculated as follows :

$$\frac{\partial C}{\partial \theta} = 750293.04(1+r)^{t-2010} + 6567.91(1-(\frac{0.9192 \cdot (t-2010)+26.45}{100})) + 21184010.46 \tag{9}$$

Clearly, Equation (6) is a monotonically increasing function with respect to the impact of competition from other industries, θ. According to relevant studies, HPC is considered a critical strategic resource for many nations, and its development heavily relies on substantial energy inputs. Currently, there is no evidence of significant energy competition among countries. Meanwhile, HPC facilities and organizations worldwide are striving for higher energy efficiency and more sustainable energy sources, which collectively reduce the likelihood of energy competition to the greatest extent possible.

5.3.3. *Exploring the impact of different energy sources and mixes on the model*

To explore the impact of the potential for different energy sources and mixes on the model, we assume that the emergence of alternative energy sources would share similarities with renewable energy. Such sources are likely to have low carbon emission factors and be readily accessible and storable. For simplicity in this discussion, we consider the potential for different energy sources and mixes as equivalent to an increase in the proportion of renewable energy. Taking the partial derivative of $C)$ with respect to ρ yields the following:

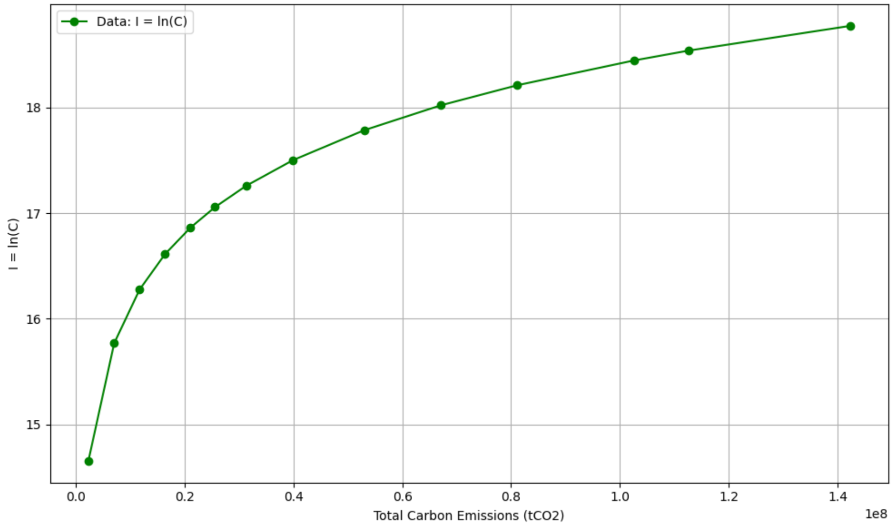

Figure 12: The relationship between environmental impact of global carbon emissions I and carbon emissions from HPC energy consumption C.

$$\frac{\partial C}{\partial \rho} = -6567.91\theta \tag{10}$$

Clearly, global HPC carbon emissions are a monotonically decreasing function of the proportion of renewable energy ρ. As the proportion of renewable energy increases, the relative consumption of fossil fuels decreases. Given the lower carbon emission factor of renewable energy, this shift can effectively reduce the total global HPC carbon emissions.

5.4. Model prediction : Insights into HPC carbon emissions in 2030

According to Equation (6), by setting t to 2030, the total global HPC carbon emissions for that year can be calculated as follows :

$$\begin{aligned} C_{2030} = &750293.04(1+0.4946)^{2030-2010} + 6567.91(1-(\frac{0.9192\cdot(t-2010)+26.45}{100}) \\ &+ 21184010.46 = 2342483383.33 \end{aligned} \tag{11}$$

Using Equation (6), we can plot the relationship between the total global HPC carbon emissions and time from 2025 to 2035, as shown in Fig.14.

From the perspective of the proportion of HPC carbon emissions to global total carbon emissions, the known data shows that in 2023, global HPC carbon emissions were 160521583.33 tCO2, while the total global carbon emissions were approximately $40.5 \times 10^9 tCO2$[14][15]. This indicates that HPC accounted for 3.51% of total carbon emissions in 2023.

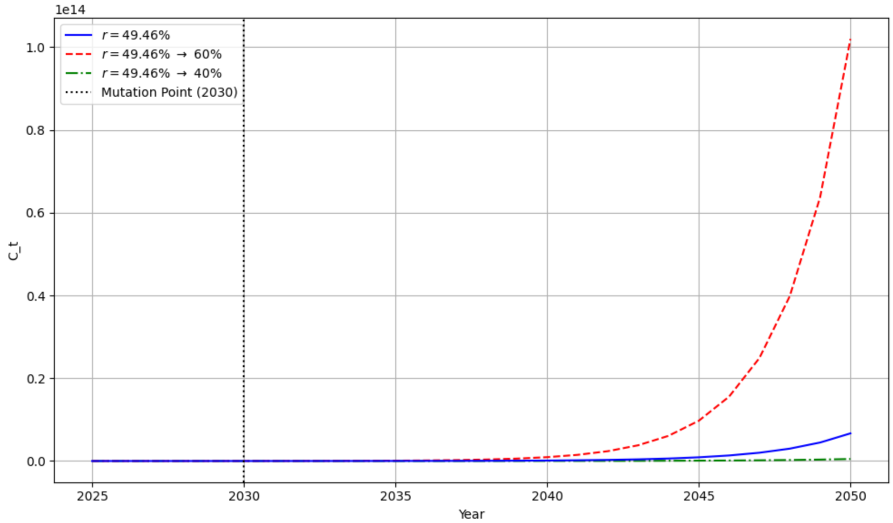

Figure 13: Exploring the Impact of HPC Growth r on Model Variations.

According to projections, global HPC carbon emissions will increase to 2342483383.33 tCO2 by 2030, while the total global carbon emissions are expected to reach $45 \times 10^9 tCO2$[16][17]. This means that by 2030, the proportion of HPC emissions will rise to 5.21% of global total emissions. This nearly 2% increase over a few years highlights the growing role of HPC facilities in global carbon emissions.

This trend suggests that HPC is rapidly becoming a major source of carbon emissions. With the rapid growth in demand for artificial intelligence, big data, and high-performance computing, HPC development is inevitably driving up carbon emissions globally. If this trend continues, countries will face increasing pressure to reduce emissions from the HPC sector.

From the perspective of the renewable energy proportion, analyzing HPC carbon emissions reveals that changes in the energy mix significantly impact carbon emission intensity. According to the equation $\rho = 0.9192 \cdot (t - 2010) + 26.45$. There are notable regional differences in the proportion of renewable energy worldwide. For example, Nordic countries such as Norway and Sweden have renewable energy proportions exceeding 80%[18], resulting in significantly lower HPC carbon emission intensity compared to the global average. In contrast, developing countries with slower energy transition processes have much lower renewable energy proportions. Prioritizing the deployment of HPC facilities in regions with higher clean energy proportions can effectively reduce total carbon emissions.

To better leverage the increasing proportion of renewable energy, countries can adopt various measures. For instance, encouraging HPC data centers to directly utilize clean energy sources such as solar or wind power, and promoting energy allocation systems that prioritize renewable energy for HPC facilities. Tax incentives or subsidies can also support the construction of local distributed energy systems, such as solar power installations, for HPC facilities. Additionally, establishing an international Green HPC Alliance to focus on deploying HPC projects in regions with higher renewable energy proportions is an effective strategy.

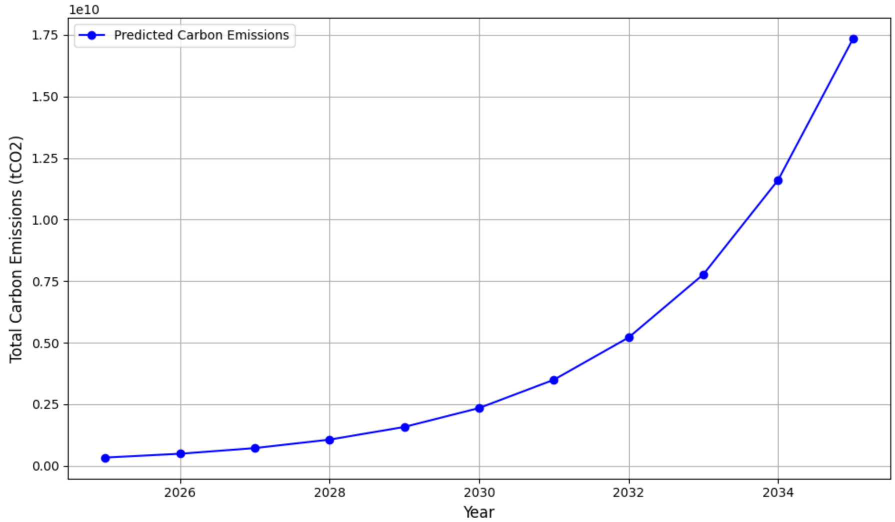

Figure 14: Predicted values for global HPC carbon emissions C from 2025 to 2035.

6. Requirement 4 : Expand the MFD-HPC Model and Conduct Further Analysis

6.1. Comprehensive exploration of renewable energy

6.1.1. *Quantitative analysis*

To simulate the impact of increasing the proportion of renewable energy on global HPC carbon emissions, we need to plot the function of global HPC carbon emissions (C) with respect to the proportion of renewable energy (ρ). We assign ρ values of 40%, 60%, and 80% to observe the rate of change in the function. When the proportion of renewable energy is relatively low, meaning fossil fuels still dominate the energy mix, global HPC carbon emissions remain relatively stable around a value of 1 despite changes in ρ. To emphasize the impact of increasing renewable energy proportions, we applied a simple adjustment to the graph, as shown in Fig.15.

From Fig.15, it can be observed that by 2035, as the proportion of renewable energy (ρ) increases from its original value of 26% to 40%, 60%, and 80%, the total global HPC carbon emissions undergo corresponding changes. As ρ rises, carbon emissions decrease relatively; however, the overall trend remains upward, driven primarily by the growth of HPC.

Incorporating our proposed MFD-HPC Model, we have derived the following information:

Initial value : $\rho(2010) = \frac{0.9192\cdot(2010-2010)+26.45}{100}$ = 0.2645.

Annual growth rate : $\triangle\rho = 0.9192$

When $t = 2030$, $\rho(2030) = \frac{0.9192(2030-2010)+26.45}{100}$

The proportion of renewable energy will reach 100% in year T : $\rho(T) = 0$, $T = 2090$

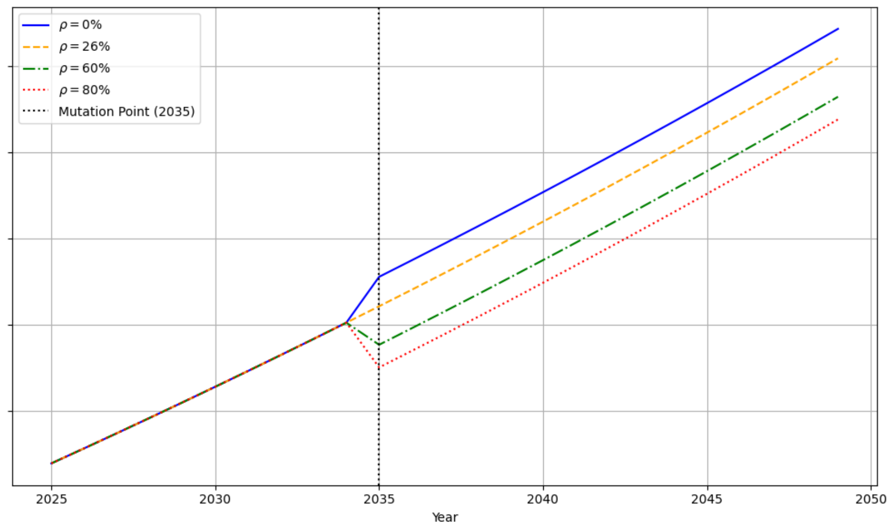

Figure 15: C_t Curves for Different ρ Values (2025-2050).

Furthermore, when the proportion of renewable energy (ρ) reaches 100% and reliance on fossil fuels and nuclear energy is eliminated, competition from other industries for energy can be disregarded due to energy saturation. In this case, global HPC carbon emissions will depend solely on the growth of HPC. As a result, the previously defined functional relationship between global HPC carbon emissions and time, expressed in Equation (5), will be simplified to the following Equation (12):

$$C_t = m \cdot (1+r)^{t-2010} + s \tag{12}$$

In conclusion, from a quantitative analysis perspective, the proportion of renewable energy has increased from 26.45% in 2010 at an annual growth rate of 0.9192%, projected to reach 44.83% by 2030 and 100% by 2090. During this process, carbon emissions associated with fossil fuels gradually decrease and will be entirely eliminated by 2090. By 2035, when the proportion of renewable energy is approximately 76.43%, global HPC carbon emissions are primarily driven by the exponential growth of HPC, with the terms in the carbon emission formula related to fossil fuel proportions approaching zero.

When the proportion of renewable energy reaches 100%, the carbon emission formula simplifies to: $C_t = m \cdot (1+r)^{t-2010} + s$. Where carbon emissions are solely controlled by the HPC growth rate ($r = 0.4946$). Although emissions continue to rise, the growth rate decreases significantly. This indicates that increasing the proportion of renewable energy has a clear mitigating effect on carbon emissions, but the growing demand for HPC remains the primary driver of future emissions.

6.1.2. *Qualitative analysis*

Transitioning to 100% renewable energy is a critical goal for reducing carbon emissions and addressing climate change. From a modeling perspective, the fossil fuel-related components of the carbon emission function will disappear entirely, leaving future emissions dependent solely on the growth rate of HPC and baseline emission levels. This shift can significantly reduce carbon emissions, making them more reliant on the exponential growth trend of HPC. However, even with a complete transition, the rapid development of HPC may still lead to a slow increase in total emissions.

Despite the significant benefits of transitioning to 100% renewable energy, the process faces numerous challenges. The first is technical. The intermittent nature of renewable energy poses a major obstacle to power stability. HPC data centers require highly reliable power supply, necessitating the large-scale deployment of energy storage systems to handle fluctuations. Additionally, existing power grids need to be upgraded to accommodate distributed energy integration and transmission. These technical demands are not only complex but also require substantial investment in research and engineering.

The economic cost is another critical challenge. Transitioning to 100% renewable energy involves building extensive solar power plants, wind farms, and energy storage infrastructure, requiring significant initial investment. Furthermore, the long-term maintenance costs and replacement cycles of these facilities may increase overall expenditures, particularly in regions where technology is not yet fully mature. For developing countries, the high financial requirements could become a major barrier, exacerbating the global imbalance in the energy transition.

Social and policy issues also arise during the transition. The uneven distribution of renewable energy resources means that some regions may find it easier to achieve energy transition, while others face both technical and resource constraints. This disparity could lead to inequities in energy use, with developing countries relying more heavily on traditional energy sources. Additionally, policy uncertainty may slow the pace of the transition. While many countries have introduced subsidies and tax incentives, long-term stable policy support is essential for achieving this goal.

Finally, from an environmental and resource perspective, the renewable energy transition is not entirely "green." The production of solar panels and wind turbines requires rare metals, the extraction and processing of which may cause new environmental problems. Furthermore, as these devices eventually reach the end of their life cycle, managing their waste will become a significant challenge.

Nevertheless, transitioning fully to 100% renewable energy remains a necessary path to achieving a low-carbon future. By implementing the transition in phases, starting with gradually increasing the proportion of renewable energy and investing in storage technologies and smart grid upgrades, technical and economic bottlenecks can be mitigated. Additionally, international cooperation and support from developed countries in terms of funding and technology can help developing countries overcome resource and economic challenges. Policymakers must ensure long-term, stable incentive mechanisms to give businesses and society the confidence needed to collectively advance this historic energy transition.

6.2. Expanding the original model into a comprehensive environmental model

6.2.1. *Key environmental challenges of HPC: Water usage and e-waste*

Based on relevant data, we found that the environmental impact of HPC, beyond carbon emissions, primarily stems from water usage and e-waste. Therefore, our model extension focuses on these two aspects. To better understand the environmental impact of HPC's water usage and e-waste, we reviewed the literature and summarized the key points as follows.

First, HPC data centers consume large amounts of water for cooling, particularly in high-temperature regions or during periods of intensive electricity use. This high water demand can exacerbate local water shortages, threatening ecosystems and human access to safe water. Second, the rapid upgrade cycles of HPC hardware produce substantial quantities of electronic waste. These discarded materials contain toxic substances, such as lead and mercury, as well as rare metals like cobalt and nickel. Improper recycling can lead to soil contamination, water pollution, and resource depletion, posing long-term threats to ecosystems and human health. Thus, HPC's issues with water usage and electronic waste not only affect the natural environment but also touch upon the broader aspects of social and economic sustainability.

We have chosen water usage and electronic waste as the focus of our analysis because these two areas are closely tied to energy consumption and reflect the multidimensional environmental impact of HPC. Water usage directly depends on the energy consumption of HPC data centers, as cooling system water requirements are proportional to energy use. The higher the energy consumption, the greater the cooling demand, intensifying water resource pressures. Meanwhile, electronic waste is linked to hardware manufacturing and replacement cycles, which themselves require significant energy. Additionally, improper handling of discarded hardware can result in rare metal waste and environmental pollution.

These two aspects illustrate the broader environmental implications of HPC and their strong correlation with other critical areas, such as resource depletion and land use. For instance, high water consumption may conflict with local land development, while the efficiency of electronic waste recycling determines the degree of rare resource reutilization. Therefore, water usage and electronic waste serve as key entry points for comprehensively understanding HPC's environmental impact and provide critical insights for energy management and policymaking.

6.2.2. *Model extension and improvement*

Based on relevant data and literature, we define the water usage model (W_t) and the electronic waste model (W_e) as shown in Equations (13) and (14):

$$W_t = w \cdot E_{HPC} + v \tag{13}$$

Here, w represents the conversion factor between water usage and energy consumption (liters per MWh), and v denotes the baseline water usage, which remains constant regardless of energy consumption.

$$W_e = \frac{\sum e_i M_i}{L_i} \tag{14}$$

Here, e_i represents the environmental pollution coefficient of different HPC hardware, M_i is the mass of various HPC hardware components (e.g., servers, storage devices), and L_i is the average lifecycle of the respective hardware.

Based on Equation (7)(11)(13)(14), the functional relationship between HPC's environmental impact and the plotted function is as follows:

$$I = \omega_1 \cdot (a \cdot lnC + b) + \omega_2 \cdot W_t + \omega \cdot W_e \tag{15}$$

$$I = \omega_1 \cdot (a \cdot lnC + b) + \omega_2 \cdot (w \cdot E_{HPC} + v) + \omega_3 \cdot (\frac{\sum e_i M_i}{L_i})) \tag{16}$$

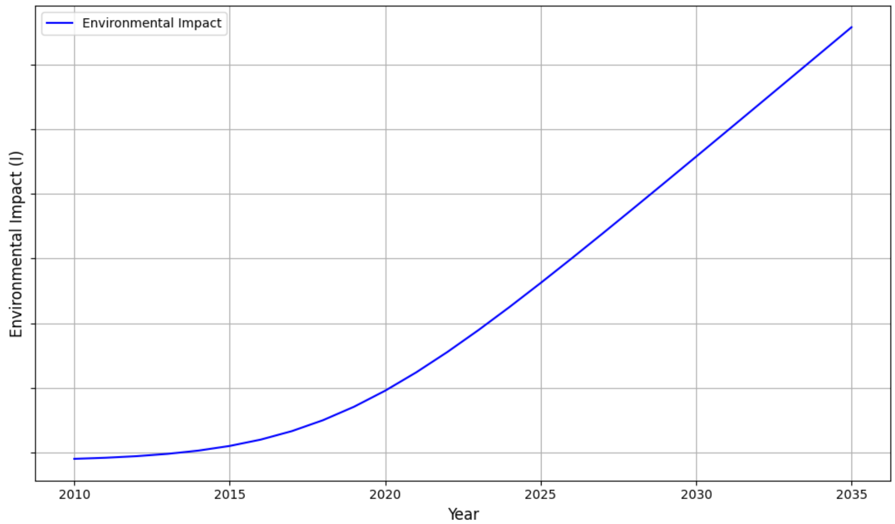

Figure 16: Environmental Impact I Over Time (2010-2035).

7. Requirement 5 : Share the Model and its Results

7.1. Actionable recommendations for reducing the environmental impact of HPC

In order to reduce the environmental impact of HPC facilities, our team developed a set of practical and actionable solutions:

1. First, the most apparent solution is to simply transit the energy used by HPC facilities from a mix of unrenewable and renewable energy to 100% renewable energy or lower the component of unrenewable resources as much as possible. This will be sure to decrease the environmental impact of HPC facilities and also corresponds to the environment-friendly theme of the government.

2. Second, we can upgrade the hardware of HPC facilities to increase the energy-consuming efficiency of HPCs. The government can encourage HPC facilities to apply more energy-efficient technologies, for example, more advanced water-cooling systems and more advanced servers. In this way, the same amount of energy can be used to sustain the facilities for more time, which saves energy in the other way, protecting the environment.

3. Third, require new environmental impact assessments for future HPC facilities or data center projects. When applying stricter environmental impact assessments to planned HPC facilities, the government can force companies to consider environment-friendly energy mixes and technologies, which can mitigate potential environmental consequences.

4. Last, we can recycle the electronic wastes and non-electronic wastes of HPC facilities, like old, outdated server components or used cooling water. By recycling electronic waste, we can save

materials while constructing new data centers or other HPC facilities, and by using cooling water, we can reduce water consumption in HPC facilities.

In conclusion, the environmental impact of HPC facilities can be reduced by applying the following recommendations: transition to renewable resources, energy-efficient hardware upgrade, new environment impact assessment, and the recycling of wastes.

7.2. Incorporating recommended solutions into the mode

For our proposed suggestion 1, optimizing the energy structure to reduce the proportion of non-renewable energy, the transformation of our model Equation (5) is expressed as follows:

$$C_t = \theta[m \cdot (1+r)^{t-2010} + n \cdot (1-\rho(t)) + s] \tag{17}$$

In our established model, the energy structure has already been incorporated, with the proportion of renewable energy varying over time. However, we simplified this variation using a linear relationship. In reality, changes in the energy structure are influenced by factors such as national policies and technological advancements, and they do not necessarily follow a straightforward linear trend. To accurately describe the relationship between energy structure and time, it is essential to consider a combination of local circumstances, geographical factors, and other relevant conditions.

Based on our suggestion 2, upgrading hardware to improve energy efficiency, and the enhancement of HPC efficiency through more advanced hardware will impact Equations (2), (14), and (16). The revised model is as follows:

$$E'_{HPC} = \eta \cdot E_{HPC} \tag{18}$$

$$W'_e = \frac{\sum e_i M_i}{L'_i} \tag{19}$$

$$I = \omega_1 \cdot (a \cdot lnC + b) + \omega_2 \cdot (w \cdot E_{HPC} + v) + \omega_3 \cdot (\frac{\sum e_i M_i}{L'_i})) \tag{20}$$

Here, η represents the proportion of improvement in energy efficiency, and L'_i denotes the extended hardware lifespan resulting from technological advancements.

Based on our third recommendation, the introduction of the Environmental Impact Assessment (EIA) aims to improve energy structures and technological choices through mandatory mechanisms. By implementing dynamic constraints, such as carbon emission limits, energy consumption caps, water resource usage restrictions, and electronic waste management standards tailored to specific countries or regions, the impact can be effectively quantified. The revised model is as follows:

$$\begin{aligned} & I = \omega_1 \cdot (a \cdot \ln C + b) + \omega_2 \cdot W_t + \omega \cdot W_e \\ & \text{subject to:} \quad C \leq C_{\text{MAX}}, \quad E_{\text{HPC}} \leq E_{\text{MAX}}, \quad W_t \leq W_{\text{MAX}}, \quad \frac{\sum e_i M_i}{L_i} \leq E_{W_{\text{MAX}}} \end{aligned} \tag{21}$$

Building on our fourth recommendation, which involves recycling the electronic and non-electronic waste generated by HPC facilities, the model undergoes the following modifications due to the recycling and reuse of electronic waste and cooling water:

$$W_t = w \cdot E_{HPC} - \delta_t + v \tag{22}$$

$$\begin{aligned} W_e &= \frac{\sum e_i M_i}{L_i} - \delta_e \\ \delta_e &= \phi \cdot M_i \end{aligned} \tag{23}$$

Here, δ_t represents the reduction in water consumption achieved by recycling cooling water, δ_e denotes the reduction in electronic waste through recycling and reuse, which is proportional to the total mass of discarded hardware, and ϕ indicates the recycling rate.

In conclusion, incorporating our proposed recommendations and the modifications to the carbon emission, water usage, and electronic waste components of the model, the final environmental impact model equation is as follows.

The total environmental impact model is given by:

$$\begin{aligned} I' = \omega_1 \cdot \ln \left[m \cdot (1+r)^{t-2010} + n \cdot (1-\rho_t) + s \right] + \omega_2 \cdot \left[w \cdot (E_{HPC} \cdot \eta) - \phi_w \cdot (w \cdot E_{HPC}) + v \right] \\ + \omega_3 \cdot \left(\frac{\sum e_i M_i}{L'_i} - \phi_e \cdot M_i \right) \end{aligned} \tag{24}$$

$$\text{subject to:} \quad C \leq C_{MAX}, \quad E_{HPC} \leq E_{MAX}, \quad W_t \leq W_{MAX}, \quad \frac{\sum e_i M_i}{L_i} \leq E_{W_{MAX}} \tag{25}$$

According to the EIA, C_{MAX} represents the maximum allowable carbon emissions, as defined by environmental policies or regulatory limits. Similarly, E_{MAX} denotes the maximum allowable energy consumption, reflecting the energy cap for HPC facilities in alignment with sustainable energy targets. W_{MAX} represents the maximum allowable water usage, determined by local water resource availability and sustainability goals. $E_{w_{\text{MAX}}}$ refers to the maximum allowable electronic waste.

Here, w: Water usage per energy unit (liters per MWh). $E'_{HPC} = E_{HPC} \cdot \eta$: Energy consumption after efficiency improvements. ϕ_w: Cooling water recycling rate ($0 \leq \phi_w \leq 1$). v: Baseline water usage. M_i: Mass of each hardware component (kg). L_i: Lifetime of the hardware (years). e_i: Environmental impact factor for each hardware component. ϕ_e: Electronic waste recycling rate ($0 \leq \phi_e \leq 1$). ω_1: Importance of carbon emissions. ω_2: Importance of water usage. ω_3: Importance of electronic waste.

The above function for I' represents the adjusted environmental impact model, incorporating our proposed recommendations and modifications.

7.3. A letter to the United Nations Advisory Board

Dear United Nations Advisory Board,

We, Team 15022, are writing to urge you to include a comprehensive section on the environmental impact of HPC facilities in your scheduled developmental goals for 2030. With the accelerating development of AI and other data-processing technology, the position of HPC facilities continues to rise every day for their advanced data-processing abilities. However, we are concerned about the energy consumption and environmental impact of the growing HPC facilities. Our team has developed a model to predict and evaluate the energy consumption and environmental impact of HPC facilities. According to the prediction of our model, the situation is quite concerning.

According to reliable data sources, we divided the energy consumption of HPC facilities into two parts: energy consumed by data centers and energy consumed by data encryption. By projecting the graph after fitting the growth of energy consumption by the two portions above with the rising computing power, we found that the energy consumption of HPCs grows at an unignorable rate. After research, we discovered that most of this energy comes from carbon-emitting and non-renewable energy sources, causing a significant impact on the environment. Later, we created a model to calculate and predict the total carbon emission of HPCs globally. For example, by the year 2030, the carbon emitted by HPC facilities will rise to 2,342,483,383.33 tons, which is 5.21% of global total emissions. This nearly 2% increase over a few years highlights the growing role of HPC facilities in global carbon emissions. We predict the total carbon emissions from now to 2030. To learn about specific data in 10 years, please read the table below:

Table 2: Total Carbon Emissions from 2021 to 2030 (in million tonnes)

Year	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Emissions	83.6	114.4	160.5	229.4	332.4	486.4	716.5	1060.3	1574.3	1574.3

Moreover, our model also includes environmental impacts beyond carbon emissions. Issues such as e-waste, water usage, and noise pollution also constitute part of the environmental impact, and our model shows that these problems are yet undetermined. Addressing these problems requires support from both companies and official organizations like you.

Our team has developed some recommended solutions to address the challenges above. When urging companies to upgrade their HPC facilities' hardware, it is determined by our model that energy efficiency will increase. Upgrading other HPC-related systems like water-cooling systems and recycling electronic waste can also contribute to the reserve of resources and help achieve the goal of environment-friendly development.

In conclusion, according to the 17 SDGs of the United Nations, we strongly recommend you include a more detailed section on the environmental impacts of HPC in the scheduled developmental goals for 2030 to lower the environmental impact and energy consumption of HPC facilities globally.

Sincerely,
Team #15022

8. Strengths and Weaknesses

8.1. Strengths

Firstly, our model takes multiple factors into account, including the growth of HPC facilities, changes in energy mixes, and additional environmental consequences, meaning that we considered as many real-life aspects of carbon emissions as possible.

Secondly, our model is relatively accurate as we investigated and analyzed carbon emission data from countries all around the world. Moreover, our model is highly adaptable as it calculates the carbon emission globally, so we can expand our model without changing the majority of our model.

Thirdly, our model uses sensitivity analysis to do impact exploration. By examining factors like HPC growth rates, energy demand from other sectors, and different energy mixes, the model assesses how sensitive outcomes are to various variables, highlighting potential areas of uncertainty or volatility.

8.2. Weaknesses

Firstly, our model is a rough global overview of the carbon emissions and environmental impacts of HPC facilities, the situation may change when specifying to a particular country. For example, Norway's energy mixture is basically formed by 99 percent renewable energy, which can impact the prediction's result.

Secondly, our model does not take the carbon emitted when constructing HPC facilities or when exploiting resources into account. This may lead to a slight error when predicting the total carbon emitted by the year 2030.

Thirdly, our model requires extensive research to acquire variables related to energy consumption, carbon emissions, renewable energy integration, and other environmental indicators across different regions. Many of these data points rely on assumptions derived from previous studies and existing literature, resulting in a potential risk of incorporating inaccuracies.

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