

Quantitative Evaluation of High-Performance Computing (HPC) Energy Consumption and Environmental Impact Using Mathematical Modeling

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ABSTRACT

HPC is developing rapidly. In the context of the information age, computing power has become a key element in promoting technological innovation and economic development. This article aims to quantitatively evaluate the development prospects of HPC energy consumption and its impact on the environment through mathematical models.

First, in order to derive the annual energy consumption model, this article collected HPC energy consumption data and determined the range of the annual energy consumption index. By interpolating the missing data in the Top500 list, weighted summation was used to calculate the total number of global HPC centers. Power consumption. Calculation results show that the maximum annual energy consumption of the Top500 HPC centers is approximately 9157 GWh, while the actual average annual energy consumption is approximately 4904 GWh.

Based on the HPC energy consumption model, this paper established a carbon emission model and designed a simple carbon emission estimation model based on the energy structure of different regions. Combining the carbon emission factors of various energy sources and the energy structure of each HPC center location, we calculated the total carbon emissions of global HPC systems are 160,290 tons.

Secondly, this paper establishes an ARIMA model for HPC scale growth and predicts changes in energy structure. After passing the ADF test, KPSS test and residual autocorrelation test, the parameters are fitted and predicted. At the same time, the energy structures of China and the United States are used as represents and predicts the changes in energy consumption structure in the next six years. The results show that the total power of global HPC will reach 1433412.3 kW in 2030, and the total energy consumption will be 22602.05 GWh, carbon emissions are 6436959.31 tons. Clean energy will account for more than 45%.

Next, this paper establishes a Markov model to describe the energy structure shift to reflect mandatory policies or changes made by energy companies. In particular, it analyzes the challenges that may be faced in reaching the goal of 100% renewable energy. The results show that in with the intervention of policy and technological progress, the proportion of oil and coal consumption will decrease significantly, and natural gas, as a less polluting energy resource, can be used as a substitute in the transition period.

Analyze the needs of the cooling system of the HPC center and the consumption of water resources. Through case studies, the cooling needs of the Frontier supercomputer are demonstrated, and the impact of seasons on coolant flow and temperature is analyzed. In order to reduce the impact of the HPC center on the environment, Plans such as developing green ICT, optimizing energy management, and carbon footprint tracking were proposed. In addition, in response to the problem of coolant waste, suggestions were made to locate HPC centers in high latitudes, recycle coolant, and participate in environmental protection projects.

Finally, a model sensitivity analysis was conducted, which proved that even if there is uncertainty in the carbon emission factor data, its impact on the final carbon emissions is relatively limited, and the error does not exceed 15%.

Keywords: *Top500list; carbon emission, ARIMA; Markov Mode*

INTRODUCTION

1.1 Background

High-performance computing (HPC) involves combining computing power to achieve higher performance than a standard desktop computer ^[1]. As the demand for HPC increases in fields such as artificial intelligence, data science, and cryptocurrency mining, the associated energy consumption and carbon footprint raise people's concerns about environmental sustainability. The huge energy demand has contributed to greenhouse gas emissions. According to data from the International Energy Agency ^[3], in 2022 global HPC consumed between 240 and 340 terawatt hours of electricity accounting for about 1% to 1.3% of global electricity demand. HPC have a huge demand for energy. According to The Chartered Institute for IT ^[4], HPC equipped with HPC systems produce carbon emissions equivalent to 100 megatons of carbon dioxide each year, which is equivalent to the emissions from the entire commercial aviation industry in the United States. This data is expected to increase two to nine times over the next decade. Such high carbon emissions can lead to global warming and climate change.

Besides, the HPC energy consumption leads to other environmental impacts including water usage (for system cooling), E-waste, resource depletion, land use and air quality, etc. The United Nation has stated that when e-waste is recycled in an environmentally unfriendly way, it can release up to 1,000 different chemicals into the environment ^[5]. The equipment used in HPCs contains materials that are difficult to recycle, which can increase environmental pollution.

To address these challenges, we aim to provide quantitative indicator values (e.g., total carbon emissions, water consumption, noise pollution, etc.) for the environmental impact of HPC energy consumption based on mathematical models. The model will consider the proportion of electricity energy and the carbon emissions of each type of energy. Moreover, the change of HPC energy demand and energy structure should be taking into consideration, especially the proportion of renewable energy sources. The environmental impact model of HPC energy consumption will help us get insight into the environmental problem. We hope to meet the growing demand for computing while minimizing environmental impact, ultimately benefiting the entire industry and society.

1.2 Problem Restatement

We aim to provide quantitative indicator values of environmental impact (e.g., total carbon emissions, water usage, noise pollution, etc.) of HPC energy consumption of based on a mathematical model, taking consideration of proportion of power energy structure and carbon emissions of different power energy source.

Question 1: By collecting the data of energy consumption of the HPC, the range of annual energy consumption index of the HPC (including full capacity mode and average utilization rates).

These two indexes are deterministic for our evaluation task of environmental impact of HPC energy consumption.

Question 2: Considering the energy mixes, we design a simple estimation model of environmental impact of total carbon emissions by sum up the carbon emissions of different energy sources.

Question 3a: The growth of HPC should be describe by a model in the future. Also, the change of energy demand in other sectors and energy sources and structure should be model for future prediction. By the study on these changes, the environmental impacts of HPC on carbon emission should be re-modelled and analyzed.

Question 3b: According to the model established in this article, HPC energy consumption, energy structure and corresponding carbon emissions are predicted in 2030, so as to have a more intuitive understanding of the future HPC environment.

Question 4a: Establish an impact model of energy structure changes to analyze the changes in the environmental impact of renewable energy proportion on HPC energy consumption. Also analyze the impact of 100% renewable energy proportion and possible challenges to achieve this goal.

Question 4b: Improve the model in Question 2, analyze the environmental impact of HPC energy consumption from other aspects (such as Water Usage, E-Waste, Resource Depletion, Land Use, Chemical Use, Socioeconomic Impacts, and Noise Pollution), and analyze its relationship with other keys The relationship between areas, especially the relationship with energy.

Question 5: Based on the model and model analysis results, a series of executable suggestions are put forward on how to reduce HPC energy consumption by adjusting the energy structure, etc., thereby reducing the impact of HPC on the environment, including reducing HPC energy consumption through technological upgrading, and improving renewable energy through technological upgrading. Energy proportion, policy guidance, etc. In addition, by analyzing the changes in energy consumption growth and environmental impact caused by technological upgrading, we discuss how to further improve the model in Question 2.

1.3 Our Work

According to the requirements, our work is as follows

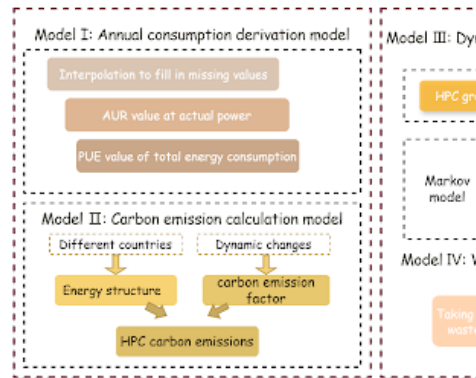


Figure 1: The flow chart of our work

2 ASSUMPTIONS AND VARIABLES

Assumption 1: All relevant data regarding the energy consumption of high-power computing (HPC) are accurate.

Justification 1: We must assume that all the data are reliable. Although some of them are just estimates, we still need to assume that they are precise in order to make our interpretations and models accurate.

Assumption 2: The PUE of all HPC centers is set to a uniform value.

Justification 2: The energy efficiency of HPC centers is related to IT equipment power consumption, cooling equipment, lighting, etc. There are differences in the energy efficiency of various HPC centers, but these differences are not significant in actual applications. This assumption helps to avoid the impact of individual HPC. It introduces unnecessary complexity due to the particularity of the center, while ensuring that the model has certain universal applicability.

Assumption 3: Replace the energy structure of the global HPC field with the energy structure of the United States and China.

Justification 3: The United States and China have important influence in the field of HPC. According to the latest data, the number of HPC in the United States and China ranks first and second in the world respectively, accounting for 51.4% of the total number of global HPC. The energy structures of the United States and China are typical. The energy structures of the United States and China represent two different energy usage patterns. The United States mainly relies on natural gas, while China mainly relies on coal.

Assumption 3: All HPC are assumed to be of equal size.

Justification 3: This article uses the number of each country/region HPC to represent its energy consumption proportion.

The variables in our paper are as list in Table1

Table 1 Definition of Variables

Variables	Meaning
P_i	Power consumption of the i-th HPC center
T	HPC center operating hours
PUE	Power usage efficiency
C	Total carbon emissions of global HPC centers
f_i	Carbon emission factor of the i-th energy source
V_i	The state vector at time
Q	state transition matrix

3 QUESTION 1: ANNUAL ENERGY CONSUMPTION

3.1 Global HPC energy consumption range description model

To estimate the range of global HPC energy consumption, this paper has selected data from the global supercomputer Top500 list in June 2024. The main variables have included the power of each supercomputer (in kW), the location of HPC centers, and HPC suppliers. Meanwhile, this study has assumed that the upper limit of energy consumption is based on all HPC centers operating at full load throughout the year, while the global average annual energy consumption has been analyzed using Frontier, the world's No.1 supercomputer, as an example by examining its real-time power consumption changes in 2023. This means that the actual utilization rate of HPC centers and supercomputers relative to their full-load state has been calculated.

3.2 Data Preprocessing and Power Estimation of HPC Center

The power of half of the HPC centers on the Top500 list is not given. For these missing data, this paper has used the rankings and known data from the list, taken the logarithm of the dataset and then fitted it with a cubic polynomial to supplement the missing values. First, using the rated power of supercomputers obtained from Top500 The List500^[1], a scatter plot has been created showing how power varies with ranking, as shown in Figure 2.

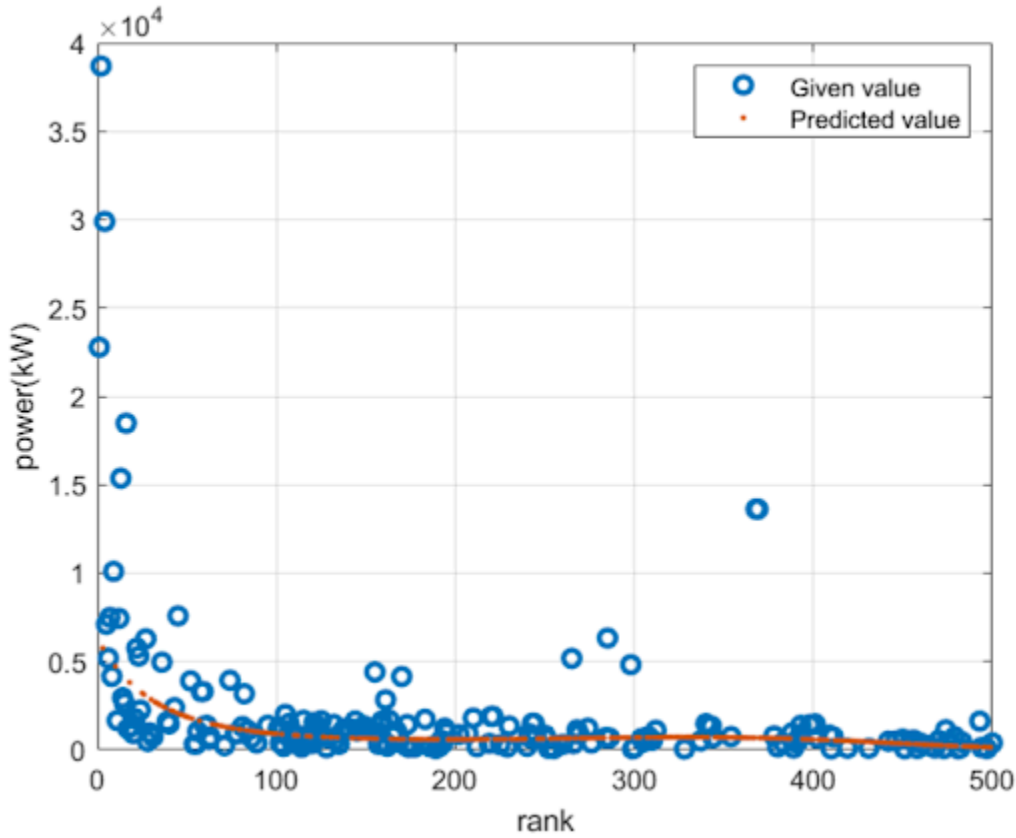


Figure 2: Scatter plot of power as a function of rank

It can be seen that there are huge differences in the power of supercomputers in different rankings. By observing the data, this paper established an exponential regression model to represent the relationship between the power and ranking of supercomputers, as shown in Equation (1)

$$P_k = e^{a_3 * k^3 + a_2 * k^2 + a_1 * k + a_0} \quad (1)$$

Using the data in Figure 1 to fit the regression function in equation (1), the functional relationship between power and ranking k is obtained

$$P_k = e^{-1.53e-7 * k^3 - 0.03k^2 + 8.75} \quad (2)$$

Where k is the ranking of the HPC center, and P_i represents the rated power of the k -th HPC center. As displayed in Figure 1, as the HPC center ranking increases, the larger the scale, the greater the total computer power of the corresponding HPC center. Then, based on the equation (2) obtained by solving the equation, the computer power of the HPC center with missing power data in the Top 500 is estimated. At the same time, based on the Top500 list and existing industry reports, it is estimated that there are currently 4,200 HPC centers worldwide^[1]. According to equation (2), the IT of HPC centers ranked outside the Top 500 can be estimated Device power. By summing the power consumption of each supercomputer in the list, the total power consumption of all HPCs in the world can be calculated. The total power consumption calculation method is as follows

$$P_{total} = \sum_{i=1}^N P_i \quad (3)$$

Where P_i is the power of the i -th supercomputer (unit: kW). Substituting $N = 500$ and the Top500 power data after interpolation, the total global HPC power is calculated to be 0.6998kW.

3.3 Average Utilization Rate

The total power of global HPC has been calculated above. However, the above power is the rated power of IT equipment. In actual operation of HPC equipment, the HPC center will not always operate at full capacity. Taking Frontier, the world's number one HPC center, as an example, we collected the power recorded every 10 minutes in 2023 and plotted Frontier's annual power data into a diagram, as shown in Figure 3.

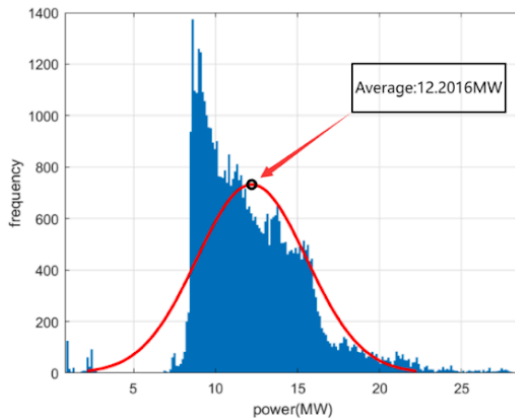


Figure 3: Scatter plot of Frontier operating power over time (time interval = 10 minutes)

Considering the actual situation, the energy consumption of HPC equipment is calculated based on acathematical expression of the AUR estimation method is shown in equation (4)

$$r = \frac{\frac{1}{N} \sum_{t=1}^N P_t}{P_{peak}} \quad (4)$$

Where P_i represents the t-th sampling point, and N represents the total number of actual operating power sampling points. P_{peak} represents the peak value of actual operating power.

By calculation, Frontier's average power is only 12.2016MW, while the TOP500 list is as high as 22.786MW. Therefore, this article calculated AUR=50%.

3.4 Energy Consumption of HPC on Full Capacity and Average Utilization Rate

According to the total power of HPC equipment worldwide, the total annual energy consumption of HPC on full capacity can be calculated as in equation (5)

$$E_{Full} = P_{total} * T \quad (5)$$

where T represents the running time (unit: hours/year), $T = 8760$ hours.

While, the total amount of energy consumption of HPC on average utilization rate is as shown in equation (6)

$$E_{avg} = P_{total} * r * T \quad (6)$$

According to equations (5) and (6), the energy consumption under full capacity and average utilization rate is calculated as follows

$$E_{Full} = 0.6998 \times 8760 \quad (7)$$

$$E_{Avg} = 0.6998 \times 0.5 \times 8760 \quad (8)$$

3.5 Total energy consumption model Considering Power Usage Effectiveness

Above, this study calculated the total energy consumption of global HPC capabilities. However, the energy consumption of HPC above only considers the energy consumption of equipment operation. In practice, the total power consumption of an HPC center includes IT equipment power consumption and non-IT equipment power consumption (such as cooling equipment, backup power supplies, lighting systems, etc.). For the energy consumption of HPC centers, a Power Usage Effectiveness (PUE) [2] metric is defined as equation (9)

$$PUE = \frac{P_{TOT}}{P_{IT}} = 1 + \frac{P_{Infrastructure}}{P_{IT}} \quad (9)$$

where P_{TOT} represents the total power of the HPC center. P_{IT} represents the power of the HPC computing device. $P_{Infrastructure}$ represents the power of non-IT equipment. PUE value has a significant impact on total power consumption. A lower PUE value indicates that the HPC center is more energy efficient. The power consumption of non-IT equipment is relatively low. The energy efficiency of each HPC center is different and not very different. A typical HPC center has a PUE value between 1.7 and 2.0. The PUE value of a good-performing HPC center can reach 1.4.

Therefore, this article assumes that $PUE = 1.6$. Rewrite the calculation method of E_{Full} and E_{avg} as equation (10) and (11)

$$E_{Full} = P_{total} * T * PUE \quad (10)$$

$$E_{Avg} = P_{total} * r * T * PUE \quad (11)$$

Bring in the data and calculate HPC energy consumption as follows

$$E_{Full} = 0.6998 \times 8760 \times 1.6 = 9808(GWh) \quad (12)$$

$$E_{Full} = 0.6998 \times 0.5 \times 8760 \times 1.6 = 4904(GWh) \quad (13)$$

Therefore, the real global HPC energy consumption of full capacity and average utilization rate should be 4904GWh and 9808GWh.

4 QUESTION 2: CARBON EMISSION MODEL CAUSED BY HPC

For the environmental impact on carbon emission (CE) model caused by HPC energy consumption, the model is a function between the total amount of energy consumption and the electricity energy carbon emission factor. Among them, there are many sources of electric energy, including two types of renewable energy and non-renewable energy. The main contributors to carbon emissions are non-renewable energy sources, such as coal, oil, and natural gas. The amount of CO₂ emitted by each energy source to produce 1 kWh of electricity is different. Therefore, for the calculation of carbon emission of HPC energy consumption, this paper considers the energy structure and energy proportion of different regions and establishes a comprehensive accounting method.

4.1 Basic CE Model

4.1.1 A Simple Model

This article calculates the carbon emissions of HPC energy consumption. The model mainly considers the carbon emissions caused by power production. Considering the energy mix, this paper establishes a carbon emission model as shown in equation (14)

$$A_{carbon} = \sum_{j=1}^m E_{Avg} * \theta_j * f_j \quad (14)$$

Where A_{carbon} represents the total carbon emissions corresponding to global HPC energy consumption. θ_j represents the proportion of the j-th electric energy source. f_j represents the carbon emission factor of the j-th energy source, which is the carbon emission of 1 kWh produced by the j-th energy source, in kg/kWh.

4.1.2 CE Model Considering Region Difference of Energy Mix

In addition, considering the differences in the proportion of power production source structures in different countries/regions, the specific calculation process needs to combine the energy structure of each HPC center location. The energy structure of each region is different, mainly depending on the source of electricity production in the region (such as coal, natural gas, renewable energy, etc.). The carbon emission factor (unit: kgCO₂/kWh) of each energy source is also different. Through this method, the carbon emissions of HPC centers can be calculated. The calculation formula of total carbon emissions is shown in equation (15)

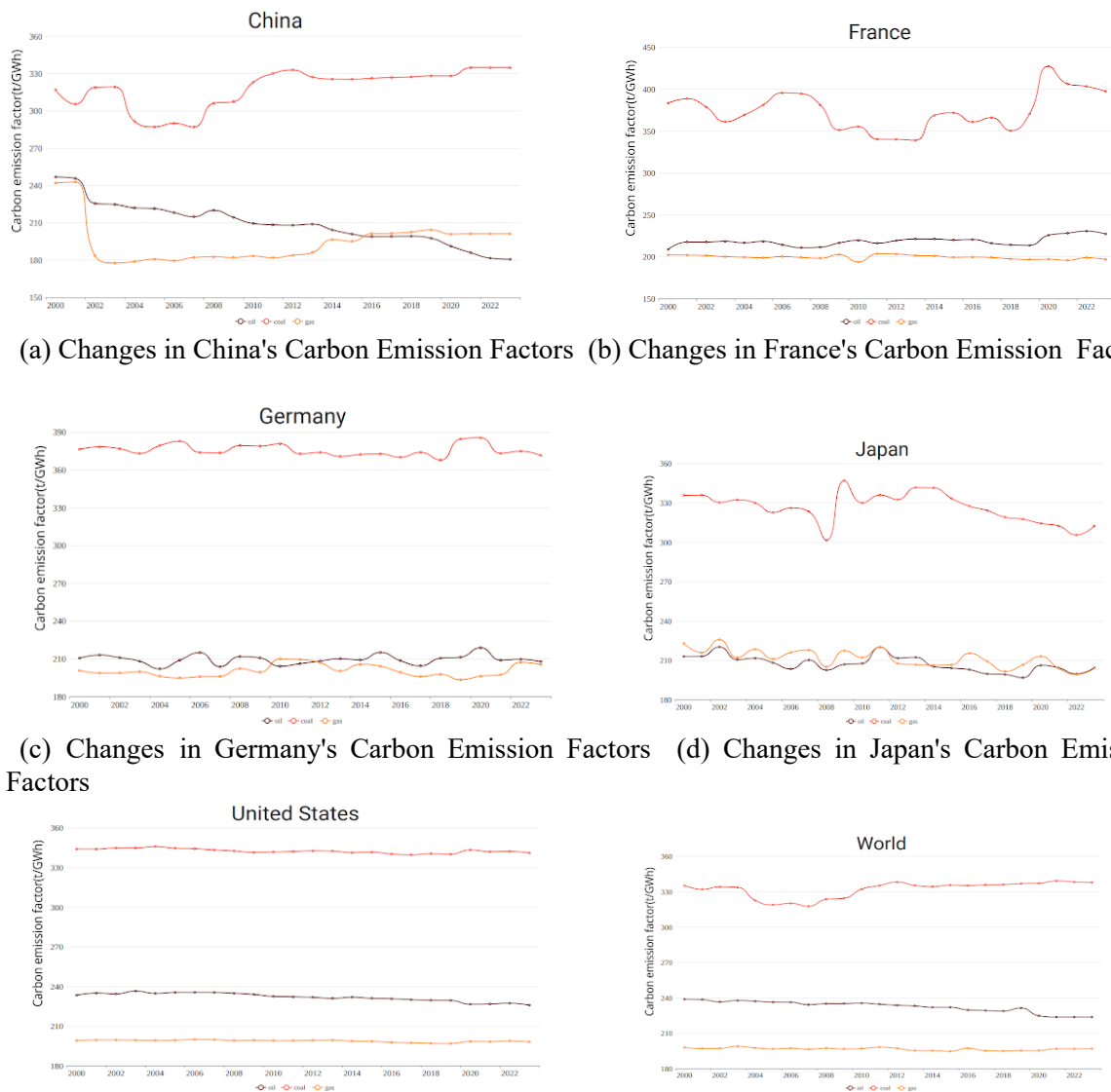
$$A_{carbon} = \sum_{i=1}^n \sum_{j=1}^m E_{Avg} * R_i * \theta_{i,j} * f_j \quad (15)$$

Where R_i represents the energy consumption proportion of HPC in the i-th region, and $\theta_{i,j}$ represents the proportion of the j-th energy source in the i-th region.

In equation (14), this paper establishes a principle model for calculating the total carbon emissions caused by HPC energy consumption. It can be seen from the model that factors affecting total carbon emissions include, total energy consumption, shares of HPC by regions, energy mixes by regions and the carbon emission factors. It is worth noting that the above four factors will change over time. The following will establish dynamic carbon emission models based on changes in HPC share, HPC energy consumption, and Energy Mixes.

4.1.3 Calculation of carbon emission factors under dynamic changes in energy structure

According to the Emission Factor Database released by IPCC, the carbon emission factor data of different energy sources in various countries were collected and sorted, and the dynamic change diagram shown in Figure 4 was drawn.



(a) Changes in China's Carbon Emission Factors (b) Changes in France's Carbon Emission Factors

(c) Changes in Germany's Carbon Emission Factors (d) Changes in Japan's Carbon Emission Factors

(e) Changes in United States's Carbon Emission Factors (f) Changes in World's Carbon Emission Factors

Figure 4: Changes in energy carbon emission factors across countries

By analyzing the changing trends of carbon emission factors in the top five countries (China, France, Germany, Japan, and the United States) and the world in terms of HPC volume from 2000 to 2023, the following characteristics were obtained: China's carbon emission factors showed an overall downward trend, especially in 2005. The decline was obvious after 2011; the carbon emission factors of France and Germany were relatively stable and at a low level, reflecting their high proportion of clean energy; Japan experienced fluctuations after 2011, which may be related to energy policy

adjustments; the carbon emission factors of the United States showed a slow but continuous trend downward trend; the overall global trend shows a moderate decline.

Based on historical data and actual conditions, the calculation results of carbon emission factors for various energy sources are shown in Table 2.

Table 2: Carbon emission factor calculation results

Energy type	Carbon emission factor (approximate)
Oil	0.2 - 0.3
Gas	0.1 - 0.2
Coal	0.8 - 1.0
Nuclear energy	0(extremely low)
Water and electricity	0(extremely low)
Renewable energy	0(Wind, photovoltaic, etc., extremely low)

4.2 Dynamic CE Model by Change of HPC Energy Consumption

In this section, considering the impact of dynamic changes in HPC energy consumption over time on total carbon emissions, this paper establishes a Dynamic CE model on Energy Consumption as shown in equation (16)

$$A_{carbon} = \sum_{i=1}^n \sum_{j=1}^m E_{total}(t) * R_i(t) * \theta_{i,j} * f_j \quad (16)$$

As shown in equation (14), the improved model here takes into account changes in total energy consumption and the proportion of HPC in different countries/regions.

4.3 Dynamic Carbon Emission Model by Energy Mixes Change

The energy structure of different countries and regions determines their carbon emission factors. For example, countries dominated by coal have higher carbon emission factors, while countries dominated by clean energy have lower carbon emission factors. This article needs to find the regions where each HPC center is located. energy structure and apply it to carbon emission calculations.

According to Figure 5, it can be found that most of the world's TOP500 HPCs are distributed in North America, the Asia-Pacific region, and Western Europe. Among them, 171 HPCs are deployed in the United States, 86 in China, 40 in Germany, 29 in Japan, and 24 in France.

Since the energy structure of each region is significantly affected by national policies, this article selects the top five countries (the United States, France, Germany, China, Japan) with the number of HPCs in 2023 to describe the global average energy structure distribution, as shown in Figure 6.

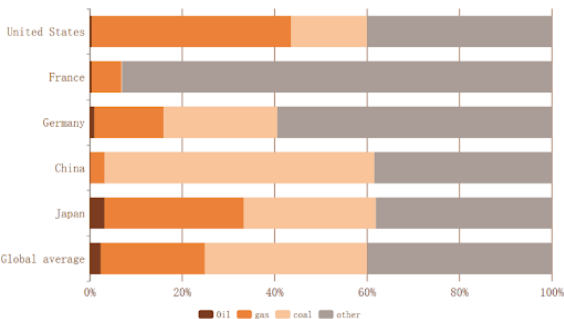


Figure 5: Distribution of Top500 HPC Centers Figure 6: Energy structure of various countries

To facilitate calculation and analysis, this article classifies energy resources with almost no carbon emissions, excluding oil, natural gas, and coal, into the other category. It can be analyzed that the carbon emissions of the United States are mainly composed of natural gas; China's carbon emissions are mainly composed of coal; Japan's natural gas and coal are in a relatively balanced state, both at around 30%; and the two European countries have the cleanest energy structures.

4.4 Example calculation

Based on the above analysis, this article selects representative data for example calculations. The data is shown in table 3. According to the data in the table, there are obvious differences in the energy structure and carbon emission factors of different regions. Among them, coal has the highest carbon emission factor, ranging from 312-397 t/GWh, followed by natural gas (196-205 t/GWh), and oil is relatively low (180-227 t/GWh). From the perspective of energy structure, China has a higher proportion of coal and Japan uses a larger proportion of natural gas. The global average shows that the proportions of oil, natural gas and coal are 0.023, 0.225 and 0.248 respectively.

Table3: Numerical table of energy carbon emission factors by country

	Oil		gas		coal	
	Ratio	CE Fators	Ratio	CE Fators	Ratio	CE Fators
China	0.001184	180.71888	0.031492	201.26144	0.608466	334.82143

France	0.003464	227.3171 8	0.062151	196.8188 4	0.164308	397.62717
Germany	0.009539	207.8228 3	0.151256	205.46311	0.001732	371.58756
Japan	0.032962	204.3316 7	0.316688	203.8990 5	0.608466	312.58977
The USA	0.003939	225.9745 3	0.431175	198.0810 4	0.300306	341.15599
Global total	0.023328	223.7525 6	0.225442	197.0013	0.248783	338.00600

Based on the deployment of the Top500 supercomputers in different regions and taking into account the differences in energy structures and emission factors in each region, the carbon emissions of all Top500 supercomputers were calculated. Substituting the above data into the CE model for calculation, the results show that the total carbon emissions of the global HPC system are 160,290 tons of CO₂. This data reflects the current carbon footprint in the field of high-performance computing and provides an important reference for future energy conservation and emission reduction.

5 QUESTION 3: HPC SCALE TIMING MODEL

As HPC technology advanced and its applications expanded, its energy consumption continued to grow, but the growth rate was constrained by energy efficiency improvements and an increase in the proportion of clean energy use. At the same time, the growth in energy demand in other industries also affected the overall energy structure, especially the need for high-energy-consuming industries to transform to low-carbon being more urgent. Taking into account the potential of different energy sources and mixes, future models needed to incorporate more variables, such as policy guidance, technological innovation, and other factors, to more accurately predict the scale and carbon emissions of HPC in 2030 and ensure that the model had practical guiding significance.

5.1 Energy Consumption Model Overview

This article collects data from the TOP500 list from June 2008 to June 2024. The following Figure 7 is the power data of the world's top 500 HPCs ranked twice a year in the past 16 years. It shows a pattern, that is, every 2 to 3 years A supercomputer has emerged that has made a step-by-step leap. Its energy consumption, performance and other parameters surpass other supercomputers of the same era.

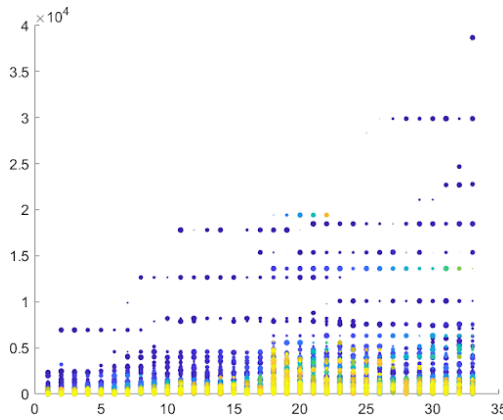


Figure 7: Top500 HPC power changes

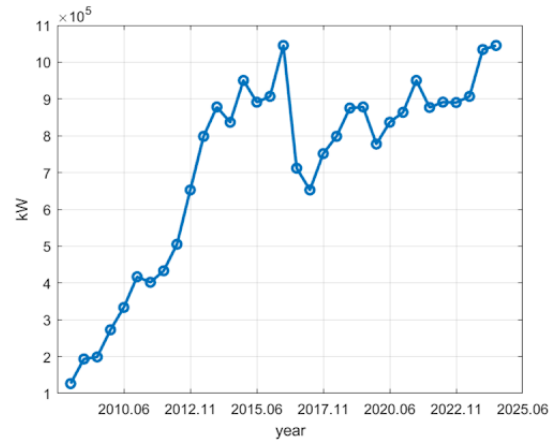


Figure 8: Average power changes in the past 20 years

By calculating the time series data of average power changes over time in the past 20 years, as shown in Figure 8, it can be seen that the time series diagram has a periodicity between 3 and 4 years, that is, in a growth cycle, the total energy consumption of global HPC first It increases rapidly, and later growth slows down until the next growth cycle arrives. It is speculated that this is caused by the long construction period of HPC, the time it takes for scientific research output to be transformed into industry, and policy influences.

After the above analysis, this article uses a seasonal time series model and an arima forecast model to simulate the cyclical changes in the global HPC construction scale under the influence of various policy and technological factors. The process is as follows

(1) First, perform the ADF test and KPSS test to test the stationarity of the time series. The test results are shown in Table 4

Table 4: Stationarity test results

	adf test	kpss test
original sequence	0	1
The sequence after first difference	1	0

Therefore, the difference order is determined to be 1.

(2) Determine the order of the ARIMA model. This article determines the order of the model based on the AIC and BIC criteria. The order of the autoregressive model is calculated to be 6, and the order of the moving average model is 6. The parameters of the final model are shown in Table 5

Table 5: ARIMA model parameters

Parameter	value
Autoregressive model order	6
Differential order	1
Moving average model order	6

(3) Use the autocorrelation function method to test the autocorrelation of the residuals and the randomness of the residual sequence, that is, make an autocorrelation function diagram of the residuals to judge the autocorrelation of the residuals. The autocorrelation function diagram is shown in Figure 9.

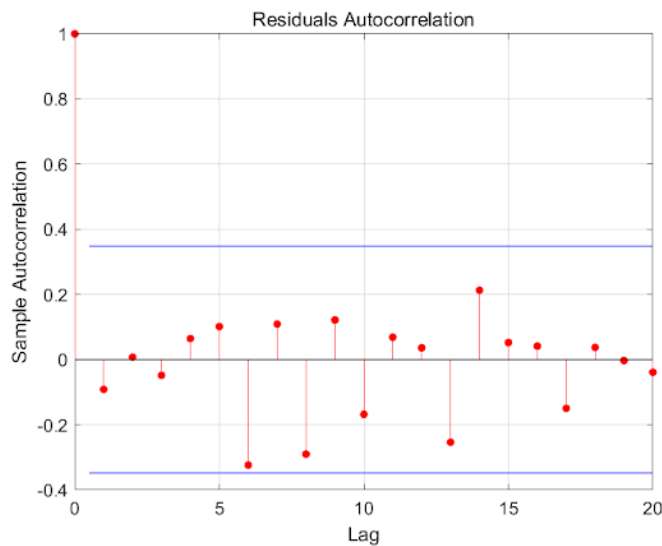


Figure 9: Autocorrelation function plot of residuals

Through the above image method, it can be determined that the residual has no obvious autocorrelation. Below, Durbin-Watson is additionally used to numerically test the correlation. From the calculation, it can be seen that the DW value of the residual is 2.1644, which is close to 2, so it is consistent with the above image method. The results are mutually corroborating and convincing.

(4) Calculation of prediction formula and determination of model parameters: On the basis of passing the above test, the Arima model of HPC energy consumption scale growth is established. The prediction formula is

$$y_t = \mu + \sum_{i=1}^6 a_i \cdot y_{t-i} + \varepsilon_t + \sum_{i=1}^6 m_i \cdot \varepsilon_{t-i} \quad (17)$$

Where y_t represents the predicted value at time t , μ represents the constant term of the model, a_i is the autoregressive coefficient, which represents the weight coefficient of the historical observation value, ε_t is the random error term at the current moment, and m_i is the moving average coefficient, which represents the historical error term. weight coefficient. Using the calculation results and inspections in the above process, the model parameters are obtained as shown in Table 6

Table 6: ARIMA model parameters

		Value	StandardError	TStatistic	PValue
AR	Constant	51.20	54.36	0.94	0.35
	a_1	-0.20	1.98	-0.10	0.92
	a_2	0.53	0.63	0.83	0.41
	a_3	-0.50	1.81	-0.27	0.78
	a_4	-0.11	1.20	-0.09	0.93
	a_5	0.59	0.67	0.88	0.38
	a_6	-0.17	1.74	-0.10	0.92
MA	m_1	0.08	1.62	0.05	0.96
	m_2	-0.92	0.72	-1.28	0.20
	m_3	0.75	2.67	0.28	0.78
	m_4	0.23	1.70	0.14	0.89
	m_5	-0.99	1.04	-0.95	0.34
	m_6	-0.16	3.12	-0.05	0.96
Variance		16385	9799.80	1.67	0.09

Based on the ARIMA timing prediction model obtained through the above process, the total power consumption of HPC in the next 6 years is predicted, and the range of the 95% confidence interval is given, as shown in Figure 10.

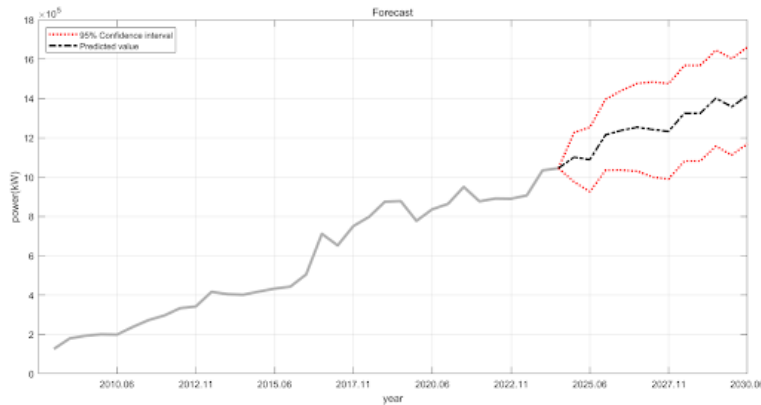


Figure 10: HPC total power consumption forecast results in the next 6 years

According to the regular fluctuations in the figure, Yi Zhi's prediction results show a 2 to 3-year cyclical fluctuation pattern, that is, in a growth cycle, the early growth is slow, and new HPC centers may be deployed and constructed, and new HPC centers may be deployed and constructed later. The HPC center has been completed and put into use, showing a trend of rapid growth in the short term.

5.2 Carbon emission time series model

The United States ranks second in the world in carbon emissions, accounting for 14.03% of the global total; the number of HPCs on the TOP500 list ranks first in the world, with 171, accounting for 34.2% of the global total. China ranks first in carbon emissions, accounting for 32.32% of the global total. HPC ranks second in the country, with 86, accounting for 17.2% of the global total. The specific situation is shown in Table 7

Table 7: Comparison of carbon emissions between China and the United States

country	Carbon emission ratio	HPC ratio	quantity	HPC power accounts for global proportion
CHN	0.3232	0.172		0.4448
USA	0.1403	0.342		0.1199

The United States and China lead the world in total carbon emissions and HPC resources. At the same time, apart from clean energy, the United States uses natural gas as its main energy resource while China uses coal as its main energy resource, which represents a dominant share of the HPC market. There are two dominant energy structures, so this article studies the changes in the energy structure of these two countries to further reflect the carbon emissions of the global energy structure.

5.3 Energy Structure Forecast

The current energy consumption structure of the United States and China from 2000 to 2022, the data includes: Coal, Oil, Natural gas, Wind, Nuclear, Hydro, etc. Since carbon emissions are almost generated by Coal, Oil, Natural gas, it will be removed. The other variables of the above three variables are identified as 'other', and the data are summarized as Coal, Oil, Natural gas, other.

Use the above ARIMA model to predict the change of each variable. After passing the test, the parameter selection situation is shown in Table 8

Table 8: Parameter selection situation

Parameter	value
Autoregressive model order	4
Differential order	1
Moving average model order	3

Based on the prediction results, the changes in various types of energy consumption in the United States from 2024 to 2030 and their 95% confidence intervals are plotted. The upper and lower bounds of the confidence intervals are represented by the red dotted lines above and below the prediction curve, where the solid line represents the predicted expected value. , and the area between the solid line and the red dotted line reflects the possible fluctuation range of the predicted value. The results are shown in Figure 11.

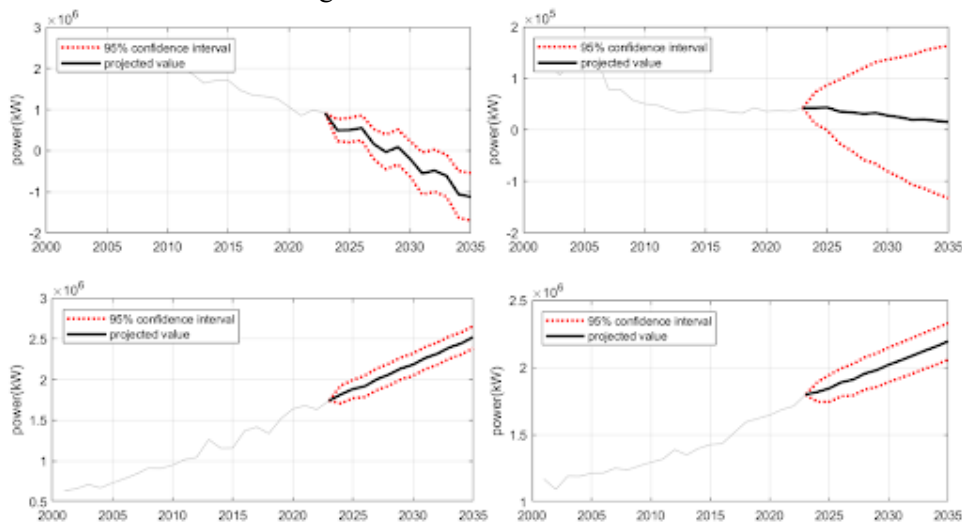


Figure 11: Forecast of U.S. energy consumption by category

We can see that Coal and Oil have declined to varying degrees and tended to zero, while Natural gas is still increasing. It can be speculated that new energy sources including nuclear energy,

wind energy, water energy, etc. cannot meet future energy needs, and natural gas still needs to be increased. use to meet U.S. energy needs. In response to changes in the energy structure, the proportion of clean energy in both China and the United States is slowly growing. Similarly, when clean energy cannot fully meet the country's energy needs, China uses coal as a substitute, and the United States uses natural gas as a substitute. The changes in the energy structure are shown in Figure 12.

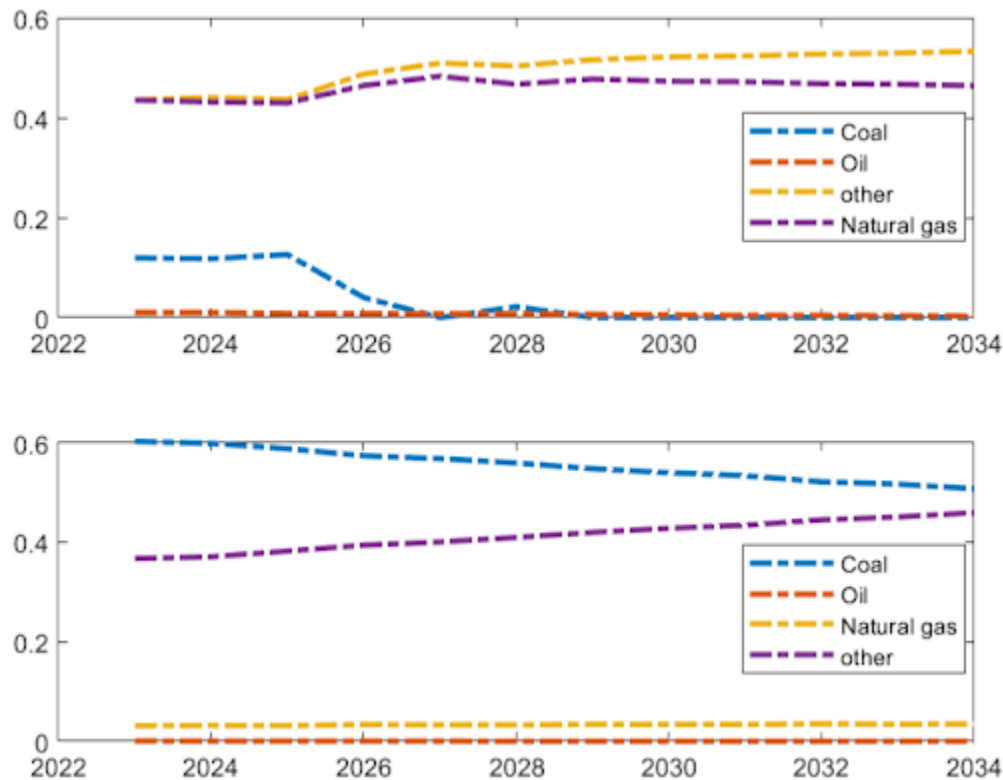


Figure 12: Changes in the energy structure of China and the United States

The transformation of the energy structure is a long-term process. In the early stage, the government and scientific research institutions need to focus on the research and practical application of clean energy. In the transition period, energy sources with large pollutants such as coal, oil, and natural gas need to be banned in a planned manner. Resource.

5.3 HPC scale and carbon emissions outlook in 2030

Based on the previous calculations, the total global HPC energy consumption in 2030 is 1433412.3kW; data provided by the National Renewable Energy Laboratory (NREL) shows that the

PUE value of the HPC has a wide range, with the overall average being around 1.8; Energy The structure is replaced by the average of the energy structure of the United States and China, and the equation (18) is obtained jointly

$$\begin{cases} E_{2030} = P_{2030} \cdot t \cdot PUE, \\ C_{2030} = (C_{coal} \cdot \theta_{coal} + C_{oil} \cdot \theta_{oil} + C_{gas} \cdot \theta_{gas} + C_{other} \cdot \theta_{other}) \cdot E_{2030} \end{cases} \quad (18)$$

Where P_{2030} is the total global power consumption in 2030, C_{2030} is the total global HPC carbon emissions in 2030; E_{2030} is the total global HPC energy consumption in 2030; C_X represents the carbon emission factor of X energy resources, and θ_X represents the Ratio of, X , $X = \text{Coal, Oil, Natural gas, other}$. The energy structure of China, the United States and the world is shown in Figure 9

Table 9: Energy structure

	Coal	Oil	Natural gas	other
America				
a	0.0000	0.0056	0.5215	0.4729
China	0.5388	0.0000	0.0338	0.4274
global	0.2694	0.0028	0.2777	0.4501

Bringing in specific numerical calculations, we can see that the total energy consumption of HPC is **22602.05GWh**, and the carbon emissions are: **6436959.31tCO₂**.

6 QUESTION 4&5: HPC ENVIRONMENTAL IMPACT AND SOLUTIONS

In the operation of HPC, the energy structure and water use had a significant impact on the environment. With the global emphasis on sustainable development, it was particularly important to study how to reduce carbon emissions by increasing the proportion of renewable energy and to optimize water use to reduce pressure on local ecosystems. To this end, this paper expanded the existing energy structure transfer model, simulated the changes in carbon emissions under different proportions of renewable energy, and explored the feasibility of 100% renewable energy and the challenges it faced. At the same time, water use was incorporated into the model to analyze its impact on energy consumption and the environment, and suggestions were put forward for optimizing the cooling system, adopting green ICT technology, and establishing an energy management system.

6.1 Energy structure transfer model

By analyzing the energy structure of China and the United States and the changing trends of various energy resources in Section 3, it could be seen that the natural gas resources in the United States had been growing, while the coal and natural gas resources in China had grown rapidly. Therefore, in the absence of regulation, energy resources with extremely high carbon emissions would continue to grow unchecked. Consequently, the Markov model was used to characterize the scenario of 100% renewable energy sources.

It could be seen that the oil, natural gas, coal, and other clean energy studied in this paper had the characteristics of mutual transformation, and the future state depended only on the current state and had nothing to do with the historical state. The above four time series variables were transformed into each other to form an undirected graph, as shown in Figure 13.

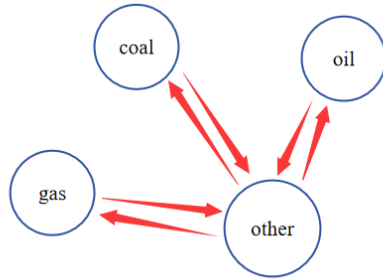


Figure 13: Undirected graph of four energy conversions

Assume that the consumption of oil, natural gas, coal and other clean energy at time i was

w_i , x_i , z_i and y_i . Respectively, $V_i = (w_i, x_i, y_i, z_i)$ let V_i be the state vector at time i , P be the state transfer matrix, a_1 , a_2 and a_3 be the transfer factors of oil, natural gas and coal respectively, then the state transfer formula was shown in equation (19) and (20)

$$V_{i+1} = V_i \cdot Q \quad (19)$$

$$Q = \begin{bmatrix} 1-a_1 & 0 & 0 & a_1 \\ 0 & 1-a_2 & 0 & a_2 \\ 0 & 0 & 1-a_3 & a_3 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (20)$$

Assuming that compulsory intervention measures were taken on the energy structure starting from 2030, such as the government issuing policies, technology or energy companies taking the lead in reform, etc., due to the long-term nature of energy reform, there were many restrictions, and the transfer factor would not exceed 0.1. Therefore, the parameter was set to: $a_1 = 0.07, a_2 = 0.04, a_3 = 0.05$, and the calculation results were shown in Figure 14.

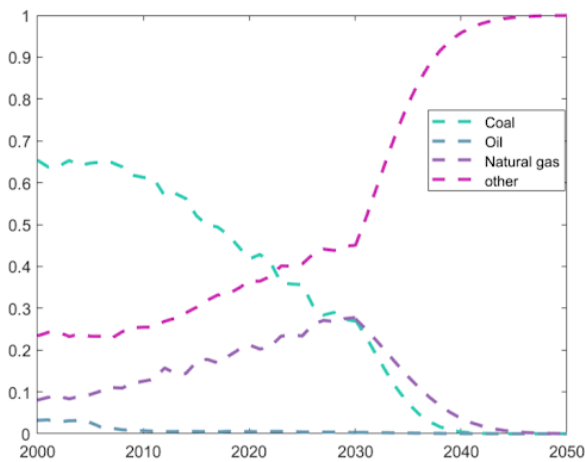


Figure 14: Energy structure shift

This showed that after the intervention, the proportion of oil consumption decreased rapidly until it was completely replaced. Coal, relying on the huge volume in the historical period, was difficult to limit, but over-reliance on traditional energy led to excessive environmental pollution. Therefore, under the intervention of policies and technological progress, the consumption of coal, a highly polluting resource, was rapidly reduced, and the proportion in the energy structure was steadily declining. Natural gas, which has low pollution and can be used as a transitional resource for clean energy, had the slowest decline rate.

6.2 Environmental impacts of water use in HPC

In addition to carbon emissions, HPC energy consumption also affected multiple environmental factors. HPC continuously released heat during operation. If the equipment was not cooled in time, it would cause failures or even damage the equipment, causing inestimable losses. Therefore, as long as HPC was running, the condensation system needed to work at all times to ensure the smooth operation of the entire HPC system.

Take Frontier in Tennessee, USA as an example. According to the data, 9,000 to 22,700 liters of water were required per minute to pass through the cooling circuit of the supercomputer to ensure effective heat dissipation, taking away 97% to 99% of the waste heat. This article plotted Frontier's condensation data records for 2023 into a graph, as shown in Figure 15.

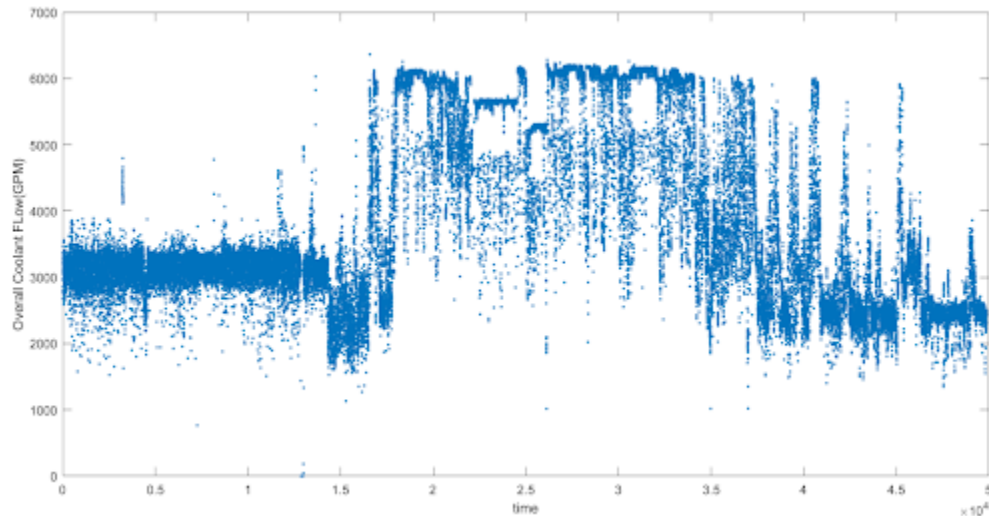


Figure 15: Frontier IT equipment condensate flow rate over time scatter plot (time interval = 10 minutes)

According to the fluctuation pattern in the figure, the coolant flow rate had significant seasonality. From January to April and from October to December, the coolant flow rate was around 300 GPM/min, while from May to August, the coolant flow rate could reach 600 GPM/min.

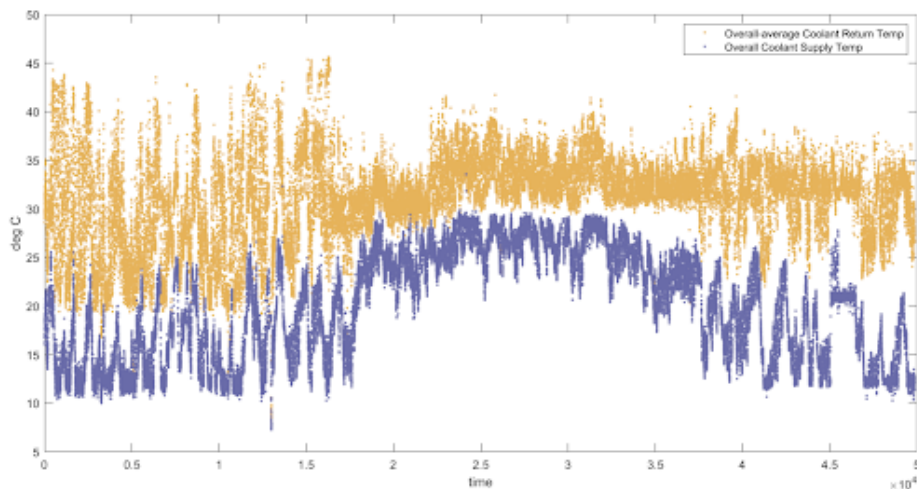


Figure 16: Coolant supply temperature and coolant return temperature over time(time interval = 10 minutes)

Figure 16 is a graph showing the change of coolant supply temperature and coolant return temperature over time in 2023. Data showed that the equipment in the HPC center allowed temperatures of 15°C to 32°C. In winter, the coolant return temperature fluctuated greatly. Since the perceived temperature was lower in winter, not too much coolant was needed to meet the temperature requirements. In summer, the perceived temperature was higher, and the coolant supply temperature also increased accordingly, requiring more coolant for cooling.

The higher the operating power of the HPC center, the more heat was dissipated, so more coolant was needed to maintain the normal operation of the system. The cooling system not only increased the operating cost of the HPC center but also created additional pressure on the environment, including water resource consumption and chemical emissions that might be generated during the operation of the cooling system.

6.2 Solution

In response to the potential environmental pollution caused by HPC, this study provided the following solutions:

- Develop green information and communication technologies, optimize the energy efficiency of computing tasks, and improve resource utilization efficiency
- Establish an energy management system to monitor and manage the energy usage of the HPC center in real time and optimize energy allocation.
- Carry out carbon footprint tracking, conduct carbon footprint tracking and auditing regularly, evaluate the carbon emissions of the HPC center, and formulate emission reduction plans.
- Policy guidance and support, the government introduces tax incentives to encourage HPC centers to adopt renewable energy and high-efficiency equipment; provide financial subsidies to support HPC centers in energy-saving transformation and technological innovation.
- Improve transparency The transparency and supervision path of the HPC center, enterprises and HPC centers regularly publish environmental performance reports of the HPC center and accept social supervision.

In response to the serious waste of coolant, this study provided the following solutions for reference:

Build the HPC center in a high-latitude area. The average temperature in high-latitude areas is lower. The data in the previous section shows that the use of coolant will be greatly reduced in a lower temperature environment. The return temperature of the coolant is basically around **40 degrees**, and it can be further processed for use by schools or companies.

HPC centers consciously participate in environmental protection and water conservation activities. For example, Frontier can participate in the Tennessee Plant Optimization Program (TNPOP), monitor coolant pollutants in real time, and learn advanced water treatment technology. And use the "plant optimization" method. Since 2011, the water resources department of the Tennessee Department of Environment and Conservation has been advocating plant optimization as an effective method with environmental and economic benefits. Improving the surrounding ecological environment through vegetation can effectively purify water resources, reduce the heat island effect, and effectively offset the pollution caused by the HPC center.

7 SENSITIVITY ANALYSIS OF THE MODEL

Performed sensitivity analysis on the carbon emission factor, changing the carbon emission factor of coal from 0.15 to 0.3 in steps of 0.01; changing the carbon emission factor of natural gas from 0.05 to 0.3 in steps of 0.01; changing the carbon emission factor of coal from 0.7 to 1.1 in steps of 0.01. Calculated the ratio of the new annual total carbon emissions in 2024 to the carbon emissions calculated in Task 2.

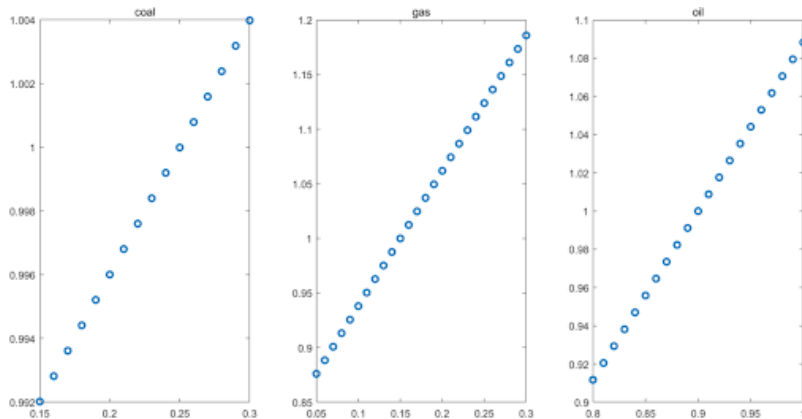


Figure 17: Sensitivity analysis of carbon emission factors

Analyzing the results in Figure 17, it could be seen that even if the carbon emission factor data might be inaccurate, the error in the final carbon emissions would not exceed 15%.

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