From HPC to Green Computing: Quantifying and Reducing Environmental Impact through Mathematical Models

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Abstract: To explore optimized high-performance computing energy consumption and environmental impact, we applied different mathematical models to solve green computing problems in distinct scenarios. First of all, we quantified global HPC energy consumption at full load by analyzing total energy consumption and power consumption across years and countries. Next, we developed a comprehensive model to estimate annual global HPC system carbon emissions based on HPC power consumption, energy mix data, and emission factors for various energy sources. Then to estimate future HPC carbon emissions, we fitted an effective Elastic Net Regression Model combining L1 and L2 regularization based on energy mix proportions, HPC energy use, and carbon emissions data from 2014–2023. The results show a peak in annual emissions in 2017 (1.456 → 1010 kg CO2), followed by a decline to 6.99 → 109 kg in 2023, indicating a shift towards renewable energy sources. In addition, using the Game Theoretical Model, we analyze competition and cooperation among HPC data centers in water resource allocation. Finally, we objectively analyzed the strengths and weaknesses of the above-mentioned model. We also drafted a non-technical report for the United Nations Advisory Board letter, using the results of our assessment and taking environmental effects into consideration.

Keywords: HPC; Elastic Network Regression; Environmental Protection; Dynamic System Modeling; Game Theory Model

1. Introduction

High performance computing (HPC, Figure 1) is a class of workloads that delivers much higher horsepower than traditional computers and servers. It's powerful enough to solve complex problems and has been applied to various fields including data management, deep learning, and quantum computing. Therefore, nowadays HPC is becoming increasingly popular, with nearly every Fortune 1000 company now using it [1].

According to Hyperion Research, the global HPC market is expected to reach $44 billion in 2022.

In practical applications, there are some loads (such as DNA sequencing) that are too large for any single computer. In most cases, HPC or supercomputing environments can enable multiple nodes to work together in a cluster to perform massive calculations in a short period of time and tackle the challenging loads of extremely complex nature. However, HPC systems typically need to operate continuously for extended periods and generate substantial heat during operation. To maintain system stability, cooling systems are essential and consume significant amounts of energy. Additionally, HPC systems often use high-power processors and GPUs, which demand large amounts of electrical power when in operation [2].

Figure 1. HPC Centre

In this paper, we aim to develop a comprehensive model to assess the environmental impact of high- powered computing, with the goal of raising awareness and promoting efforts to reduce its negative effects. To clearly show our work, we create a flowchart as shown in Figure 2.

Problem 1: For this problem, we need to conduct extensive literature review and to understand the energy consumption and the corresponding carbon footprint associated with HPC. Then we build a comprehensive model to evaluate it.

Problem 2: By comparing current energy use with environmental indicators under the model, we set a framework to assess the expected global carbon emissions and the feasibility of making a reduction in carbon emissions.

Problem 3: After that, we will use our model to predict the energy consumption and environmental impacts of replacing the current energy sources in HPC with renewable energy, assessing the expected carbon emission reductions elaborate on energy consumption. Also, we will assess the feasibility of such an operation.

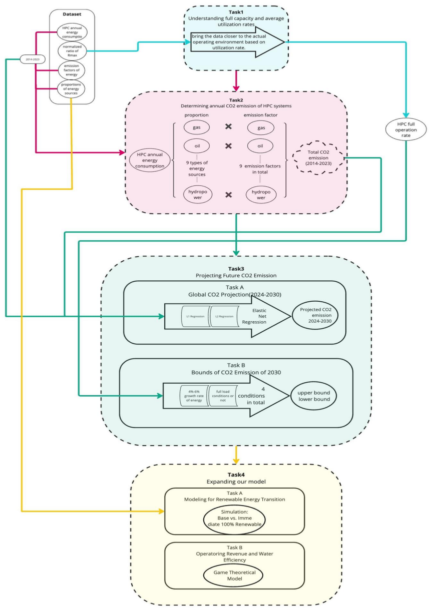

Figure 2. Flow Chart of Our Work

Problem 4: Lastly, we are required to elaborate on and apply our models to specific HPC facilities, analyzing whether the new energy policies will be adopted and if the shift is worthwhile. Based on this analysis, we will compose a report to the stakeholders of the selected facility advocating for a shift to renewable energy.

2. Mathematical Model Construction

2.1 Model Description

2.1.1 Symbols and Notations

The variables used in our modeling process are summarized in Table 1, which provides precise definitions for each parameter.

Table 1. Variable Definitions

Variable	Description
E total	Total carbon emissions (kg CO2) resulting from energy consumption of HPC facilities.
pi	Proportion of energy type i used in HPC for the given year (e.g., 50% represented as pi = 0.50).
ci	Carbon emission factor (kg CO_2 per kWh) for energy type. This represents the amount of CO_2 emitted per unit of energy consumed for each energy source.
H	Total energy consumption (kWh) of the HPC facilities for the given year.
FT	1 - RT, where RT is the proportion of renewable energy used in the total energy mix for year T.
ef	Carbon emission factor for fossil energy sources (kg CO2 per kWh).
er	Carbon emission factor for renewable energy sources (kg CO2 per kWh).
xi	Feature vector for the i-th observation (energy consumption and energy mix proportions).
yi	Observed carbon emissions for the i-th year.
λ_1 , λ_2	Regularization parameters.
$I_{C,y}$	Income value for country C in year y.
$Income_{C,y}$	Operating income for country C in year y.
$Efficiency_{C,y}$	Water-saving efficiency for country C in year y.
Et+Δt	Predicted energy consumption at time t +Δt.
Et	Energy consumption at time t.
Δg	Growth rate fluctuation, which can vary within a specified range (e.g., between -5% and 5%).

2.1.2 Data Description

We derived the dataset from a diverse range of sources. This approach ensured that the dataset was both comprehensive and representative. The data sources with full links are shown in Table 2 (Figure 3):

Table 2. Data Sources with Full Links

Category	Link
Energy Source Proportion Data	https://www.energyinst.org/statistical-review
HPC Energy	https://www.top500.org/lists/green500
Emission Factors	https://www.iea.org/data-and-statistics

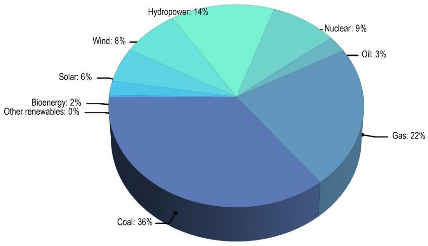

Figure 3. Energy Source Proportion of 2023

2.1.3 Assumptions and Justifications

•Assumption 1: All carbon emissions and environmental impacts are caused by high-performance computing (HPC).

•Justification 1: This assumption is made to focus solely on the environmental consequences that arise directly from HPC operations, excluding any other potential external factors that might contribute to carbon emissions or environmental degradation. By isolating HPC as the main source of environmental impact, we can more accurately analyze its role in carbon emissions and energy consumption.

•Assumption 2:We only consider the cost caused by high-performance computing in this case.

•Justification 2: This assumption is made to simplify the analysis and provide a clearer under - standing of the specific environmental and economic costs associated with HPC. By excluding other costs (such as those from other industries or sectors), we can narrow our focus and develop more precise models for the impacts of HPC on carbon emissions and resource consumption.

•Assumption 3: All data collected is accurate.

•Justification 3: The data used in this study is sourced from reputable and professional websites that provide reliable, peer-reviewed, and up-to-date statistics. While no data collection process is completely free from error, we assume the accuracy of these sources based on their credibility and the rigorous standards of the organizations behind them.

•Assumption 4: There is no other welfare loss occurring before and after refining the model, considering the new factors that influence the environmental impacts caused by HPC.

•Justification 4: In this case, we focus on the direct consequences of refining the HPC model with respect to environmental impacts. We do not account for potential social or economic welfare losses that might result from other unforeseen factors. By narrowing our scope to the impacts that are directly caused by the model refinement and the introduction of new variables, we maintain the simplicity and clarity of our analysis, while assuming no significant unintended consequences.

•Assumption 5: Ideal time consumption and steady-state conditions are assumed for all processes.

•Justification 5: The model assumes that the system operates in a steady-state, with constant performance over time. This removes the need to account for fluctuations in load or transient behaviors, which simplifies calculations. In reality, time consumption and system states may vary, but this assumption ensures a simplified and tractable model for understanding long-term trends in energy consumption and emissions.

2.2 Analysis of Global HPC Energy Consumption

2.2.1 Data Description

To conduct this study, we collected HPC energy consumption data for multiple years and different countries. The core variables of the data include Rmax (Maximum computing performance in GFLOPS), power (power demand in kW), year(year), and country(country). These data are retrieved from various CSV files and, after cleaning and integration, provide extensive geographic and temporal coverage for analysis. In each data file, Rmax is used to describe the theoretical computing power of an HPC system, and Power reflects the power requirements required to achieve this capability. The Year and Country fields provide time and space distribution information and allow data to be grouped at the annual and country levels. Through the detailed mining and integration of these data, we were able to draw a panoramic view of the world’s HPC energy consumption and laid the data foundation for subsequent task analysis.

2.2.2 Energy Consumption Framework

In the process of quantifying the energy consumption of HPC, we mainly focus on 2 key indicators. The first one refers to the theoretical maximum amount of energy which an HPC system needs in order to operate at full load during the entire year. This indicator can not only reflect the theoretical limit energy consumption of one HPC system, but also provide a criterion for measuring its peak operating efficiency. The second is the average utilization rate of energy consumption. The indicator reflects the energy demand under average conditions based on the actual operation of the HPC system and fluctuations in utilization.

By combining these two indicators, it is possible to comprehensively clarify the difference between the theoretical maximum working-situation value of HPC system and the actual operation.

The study first comprehensively prepare sand processes the original data. At this stage, make sure that all data files contain the required fields, and at the same time clean up and repair possible and invalid values. For non-numeric fields, such as numeric data stored in text format, type conversions were performed to ensure the accuracy of the calculation process. After the clean-up of the data was completed, we entered the energy calculation phase. In the calculation of full-load energy consumption, we estimate the theoretical maximum energy demand under full-load operating conditions throughout the year using the formula:

$$E_{\text{total}} = Power \times Time \qquad (1)$$

To calculate the energy consumption at the average utilization rate, the normalized ratio of Rmax was introduced and adjusted to bring the data closer to the actual operating environment based on the actual utilization rate. After obtaining the energy consumption values for each system, the data were grouped according to the year and country to calculate the total full load energy consumption and total average energy consumption for each year. This process will help you to fully understand the characteristics of HPC energy consumption from 2 dimensions: time and geography. Finally, the processed and calculated data is saved as a CSV file for further analysis and display.

2.2.3 Results

By carrying out the above methods, the study made a series of valuable discoveries. First, under full load operating conditions, the total annual energy consumption of HPC systems reaches 9,438,010.26 kWh. The results show that when all HPC facilities operate at uninterrupted peak levels throughout the year, their energy demand is very high. However, in actual operation, the average energy consumption is reduced due to load fluctuations and differences in system utilization. The calculated results show that the energy consumption adjusted based on the Rmax ratio is close to the actual situation.

In addition, analysis at the national level found that countries where HPC is deployed intensively, such as Western countries where science and technology are advanced, account for a fairly high percentage of global total energy consumption. Due to the need for technological development, these countries are highly dependent on HPC facilities, which has led to a concentration of energy demand. In developing countries, the impact of carbon emissions cannot be ignored because of the high proportion of fossil fuels in the energy structure, although the introduction of HPC facilities is relatively small.

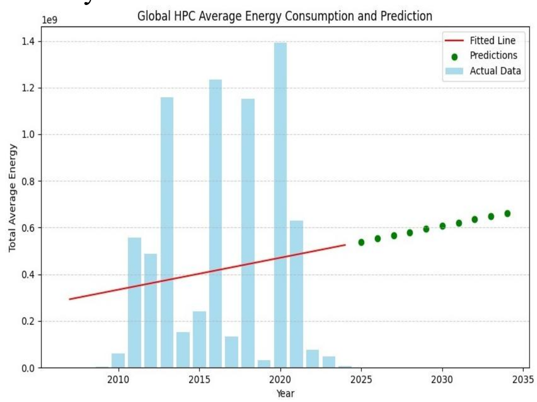

Figure 4. Global HPC Average Energy Comsumption and Prediction

Judging by the annual trend as shown in Figure 4, the growth rate of HPC energy demand is very related to the popularity of its technology applications. In particular, the energy consumption of HPC systems is increasing year by year amid a surge in demand in the fields of artificial intelligence and big data. This trend is consistent with the overall trend of global scientific and technological development.

2.2.4 Discussion

Research results show that the energy consumption of HPC systems has a multi-dimensional impact on the environment. On the one hand, the energy consumption under full load conditions provides a reference value for HPC equipment under extreme operating conditions, on the other hand, the analysis of the average operating rate reveals the energy efficiency performance in actual operation. As a result of comparing the two, it was found that there is much room for optimization in the operation of HPC system. To further reduce the energy footprint of the HPC system, they can take the following measures: The 1st is the introduction of dynamic load management technology. By dynamically adjusting the operating load of HPC according to actual needs, unnecessary energy waste can be effectively reduced. The second is the adoption of efficient heat dissipation technologies such as liquid cooling or other innovative heat dissipation solutions that help reduce energy loss in the heat dissipation process. In addition, gradually increasing the proportion of renewable energy used will significantly reduce the carbon emissions of HPC systems, especially in the context of the transformation of the energy structure.

2.3 Environmental Impact of HPC Energy Consumption

2.3.1 Current Situation

As the needs for high performance computing in artificial intelligence, data science, and cryptocurrency mining increases globally, the energy required to accomplish those massive computations experiences rapid growth accordingly [3]. This has had a huge impact on the relationship between energy assumption and the nature by far, especially demonstrated by carbon emission [4]. Yet, during the expansion of data centers around the world, carbon footprints due to HPC should no longer be considered negligible, typically when a large proportion of the energy source used in generating electricity for HPC to consume is fossil energy.

2.3.2 Data Preparation

Energy Source Proportion Data: We used data on the world's energy mix, including the proportion of different energy sources such as coal, electricity, natural gas, and renewables, as shown in Figure 5. These data help us to determine the proportion of different energy sources used to generate electricity each year.

HPC Energy: Since there is no direct data on how much power is consumed by high performance computing systems globally, we extract the data of top 500 HPC systems and use them to estimate the complete view, assuming that the top 500 systems account for 60 percent of energy consumption of all HPC systems in the world.

Emission Factors: Electricity came from different energy source will have a different extent of environmental impact when dealing with carbon emission problem, so it is necessary to clarify how much kg of carbon dioxide will be released as 1 kWh of electricity came from different sources is used.

2.3.3 Pursuing Step by Step

First, we filter the data to extract years and metrics common to all three datasets to ensure consistency. In total, we input data from 10 years (2014-2023) and 9 energy sources (bioenergy, solar, wind, hydropower, nuclear, oil, gas, coal and other renewable energy) for calculation. Second, we calculate the total carbon emissions of HPC year by year based on the annual HPC energy consumption and the proportion of each energy use, combined with the carbon emission factors of each energy. The core formula we use is:

$$E_{\text{total}} = \sum_{i=1}^{n} P_i * C_i * H \tag{2}$$

As comes to the results, we get carbon emissions that show slight fluctuations between 2014 and 2023, as shown in Table 3.

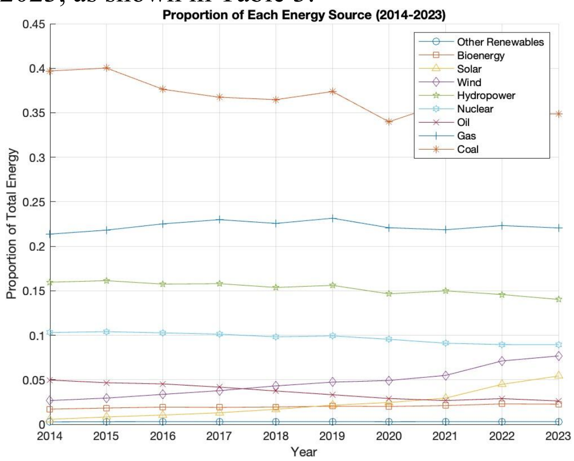

Figure 5. Changes of Proportion of Energy Source From 2014-2023

Table 3. Annual Total CO2 Emission(kg)

Year	Total CO2 Emission(kg)
2014	4.98×10^9
2015	4.69×10^9
2016	5.09×10^9
2017	1.46×10^{10}
2018	9.32×10^9
2019	8.04×10^9
2020	7.39×10^9
2021	7.38×10^9
2022	7.07×10^9
2023	6.99×10^9

2.3.4 Analysis of the Results

The Figure 6 shows the annual CO_2 emissions of HPC for 2014-2023 (in kg). From the data, we see that emissions reached the highest point in 2017 (1.456 × 1010 kg CO_2) and then slowly declined.

This could mean that, while the energy consumption of HPC facilities continues to grow, energy source structure or more efficient computing hardware may offset the resulting carbon footprint. For instance, doubling the amount of renewable energy could have had some positive effects on carbon emissions.

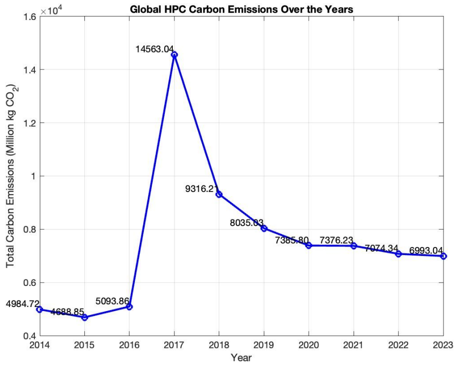

Figure 6. Global HPC Carbon Emissions Over the Years

2.4 Projecting Future CO2 Emission

2.4.1 Context of the Problem

As global demand for high-performance computing increases, HPC energy use and carbon emissions are becoming increasingly serious threats to sustainable development. As HPC systems consume large amounts of energy, particularly electricity, this directly contributes to increasing carbon emissions and contributes to global climate change. Energy composition and energy use both play complicated roles in determining carbon emissions [1]. Thus, our goal in this problem is to build a predictive model that accurately predicts HPC global carbon emissions in 2024- 2030 using historical energy mix values, annual HPC energy use and carbon emissions, and to find out how different energy elements impact carbon emissions. With the help of this model, we could give decision makers a data basis to design effective emission reduction policies and encourage the use of green energy [5].

2.4.2 Model Selection and Comparative Analysis

Here are the reasons for choosing the most appropriate model: Elastic Network Regression.

Multi-factor Modeling Capability: The advantage of elastic network regression is that it brings together both L1 (lasso regression) and L2 regularization (ridge regression) for the purpose of both variable screening and multicollinearity handling. There could be a correlation between energy structure and energy use, and so elastic network regression would be a good choice.

Robustness: Compared with the time series model, elastic network regression only cares about how dependent variables (energy share, energy usage) relate to independent variables (carbon emissions), not how time dimensions are autocorrelated. For short-term historical data between 2014-2023, elastic network regression is an optimal solution for mitigating insufficient data effects.

Explanatory: The elastic network regression coefficient can be used to quantify the individual impact of each energy on carbon emissions, useful for future policy decision making and target optimization.

Limitations of Time Series Models: The time series models like ARIMA or LSTM emphasize the time dependence of the data and can exclude key influences like energy ratio, energy use. Additionally, time series models are extremely dependent on long-term data and are difficult to interpret for underlying reasons. This model, hence, is not suitable for modeling the impact of changes in energy share in this study.

Initially we extract energy mix proportions, HPC energy consumption per year, and carbon emissions from the three data sets containing data from 2014 to 2023, convert energy proportions to percentages, and merge all variables to construct the matrix X and target variable y.

The second step is to adjust the model parameter $\alpha = 0.5$ so as to control the effects of L1 and L2 regularization. Next, build the elastic net model based on the historical data and extract the regression coefficients B and intercept.

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \left(\sum_{i=1}^{n} (y_i - X_i\beta)^2 + \lambda_1 \|\beta\|_1 + \lambda_2 \|\beta\|_2^2 \right) \quad (3)$$

After that, we assume a 5% compound annual increase in HPC energy usage. Calculate the energy mix percentages for 2024-2030 using interpolation, and estimate the carbon emissions for the next seven years using assumed energy consumption and energy mix ratios.

Finally, we plot the historical and future carbon emissions relative to each other to visualize the trends.

2.4.3 Results Analysis

The Figure 7 displays the global high-performance computing (HPC) carbon emissions forecasts between 2024 and 2030. Carbon emissions are forecast to rise from around 707 million kg in 2024 to about 832 million kg in 2030, an increase of 17.4%. Such an effect means that, as HPC energy use rises, so does its carbon footprint.

Besides the prediction results, we get the Elastic Net regression model coefficients (as shown below).

The coefficients of the Elastic Net regression model are listed in Table 4, providing insights into how different energy sources impact carbon emissions.

From them, the regression coefficient for HPC energy use is 1.3703, so the more HPC energy usage, the more carbon dioxide will be released. Additionally, other renewable energy sources (wind and solar) have a negative carbon emission coefficient, which means that they reduce carbon emissions. Fossil fuels such as oil, coal and natural gas increase carbon pollution, as their positive coefficient indicates, and the coefficients of those energy sources quantify their carbon emissions.

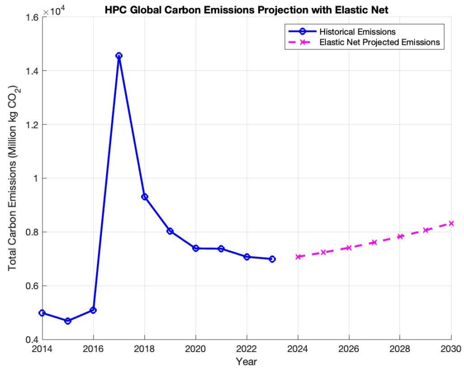

Figure 7. Elastic Net Regression Model Projection

2.4.4 Follow Up

How much energy HPC systems will use and how many tons of carbon they'll generate over the next few decades is important for policymakers and scientists when they design sustainable development plans. In this problem, we used scenario analysis to predict HPC energy and carbon consumption over time based on past performance under different growth rates and use scenarios.

We looked specifically at annual growth rates of 4% - 6% and under two use cases: 70% utilization (assuming resources were not being used) and 100% utilization (maximum efficiency). Through two-scenario approach, we could simulate conceivable variations in capacity and their effects on carbon emissions in the future.

2.4.5 Proposed Solution Steps

To address this problem, we first defined a range of growth rates (4%-6%) to calculate HPC energy consumption for the next 7 years. We estimated two use cases for each growth rate:

Scenario 1: 70% utilization, which refers to a lower level of efficiency.

Scenario 2: Full usage, which is the optimal situation.

Here are the principal steps in our model:

Projections for Growth Rates: Project HPC energy usage by year based on pre-set growth rates and utilization levels.

Energy Mix Trends: Linear interpolation for energy mix ratios in 7 years.

Carbon Emissions Estimation: Integration of regression coefficients, energy consumption, and energy proportions for future emissions, in which we used this key formula:

$$E_t + \Delta t = E_t \times (1 + \Delta g) \quad (4)$$

Cases Analysis: We combine the two growth rates (4% and 6%) with the two operating scenarios (70% and 100%) into 4 cases in total, which can help us to determine the upper bound and the lower bound of CO2 emission in next 7 years, especially 2030. We plotted results into 4 separate graphs (Figure 8, Figure 9, Figure 10, Figure 11) to visualize the range of predictions.

Our key findings include:

(1) At a 4% growth rate: Energy consumption and carbon emissions are increasing in both utilization scenarios, and 70% utilization is significantly lower emission. The case with a growth rate of 4% and a utilization rate of 70% refers to the lower bound of the prediction, as shown in Figure 8.

Table 4. Elastic Net Regression Coefficient

Feature	Coefficient
Intercept	-2.245×10^9
HPC Consumption (kWh)	1.3703
Other Renewables	-5.3435×10^{11}
Bioenergy	-1.6924×10^{11}
Solar	-6.9712×10^7
Wind	2.3324×10^8
Hydropower	$- 1.8957 \times 10^{10}$
Nuclear	-3.6537×10^{10}
Oil	1.563×10^{10}
Gas	3.0112×10^{10}
Coal	5.5049×10^9

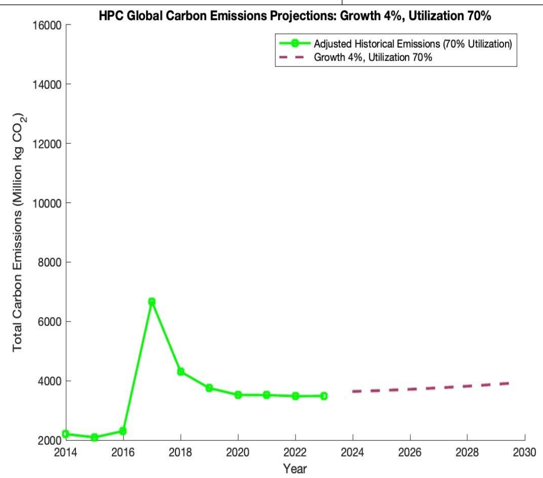

Figure 8. Growth 4%, Utilization 70%

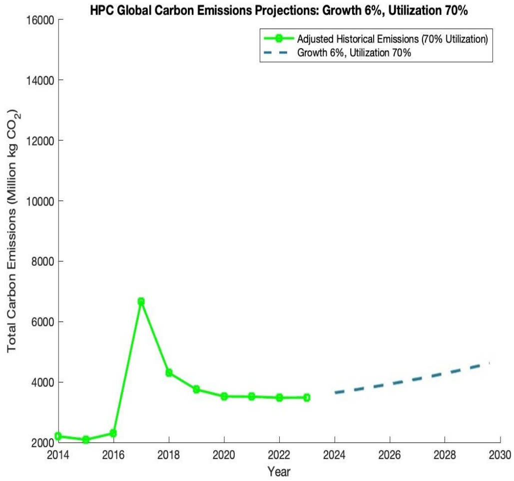

Figure 9. Growth 6%, Utilization 70%

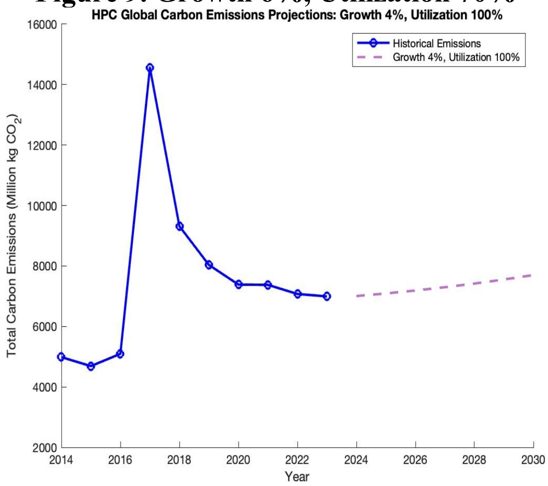

Figure 10. Growth 4%, Utilization 100%

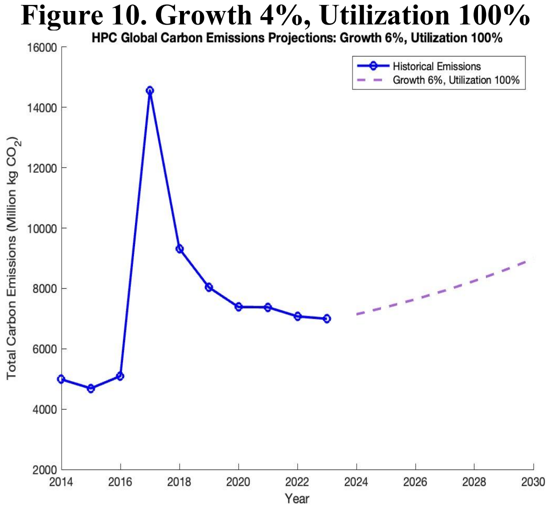

Figure 11. Growth 6%, Utilization 100%

(2) With a 6% growth rate: Carbon emissions rise rapidly in both utilization scenarios (most prominently, in the 100% utilization case) which shows how serious the impact can be on the environment. The case with a growth rate of 4% and a utilization rate of 70% refers to the lower bound of the prediction. The case with a growth rate of 6% and a utilization rate of 100% refers to the upper bound of the prediction, as shown in Figure 11.

2.5 Dynamic Modeling for Renewable Energy Transition

The background of energy transformation is not only one of the important global strategies to combat climate change, but also the key to achieving sustainable development. The current energy system is still fossil fuels, and the carbon emissions it brings are one of the main drivers of global warming [1]. Before 1, How to promote the rapid development of renewable energy through energy and technology. In the context of this article, the as a dynamic system model is a tool that can simulate changes in complex systems, and it provides important theoretical support for the equivalent analysis of processes and energy conversion [6].

2.5.1 Modeling and Methodology

Dynamic system models capture the evolutionary characteristics of energy systems under various situations with dynamic changes in energy consumption, carbon emissions, and, in essence, energy structures [7]. The input of the model includes initial energy data (such as total energy consumption, percentage of renewable energy), energy growth rate, and emission factors; the output includes the time evolution of the energy structure, trends in total energy consumption, and changes in carbon emissions [8]. The model first uses the formula:

$$p_{t+1} = p_t \times (1 + g) \quad (5)$$

To determine the annual growth rate of total energy, which reflects the change in trend energy demand. Based on this, the model also guarantees the system's ability to adopt renewable energy, the ratio of renewable energy in the form of:

$$r_{t+1} = \min(R_T + \Delta R, 1) \quad (6)$$

Finally, the carbon emissions are recalculated by the formula:

$$Pt = P_T \times (F_T \cdot e_f + R_T \cdot e_r) \quad (7)$$

The above formula describes the dynamic evolution of the energy system in terms of time and structure.

2.5.2 Scenario Analysis and Simulation Results

Scenario analysis involves simulating the transition of energy systems to renewable energy sources. The results have been shown in the Figures12-15. The proportion of renewable energy is assumed to increase by 5% annually, reaching approximately 65% of total energy by 2030. During this period, carbon emissions gradually decline, with total emissions reduced by 40%. However, dependence on fossil fuels constrains further system optimization. This scenario reflects the potential of a gradual transformation path while highlighting its environmental benefits.

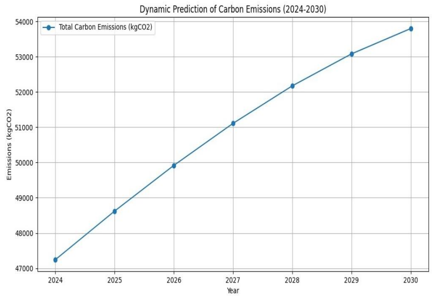

Figure 12. Dynamic Prediction of Carbon Emissions

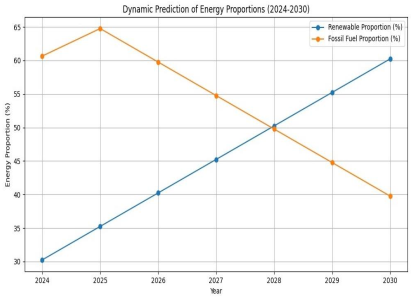

Figure 13. Dynamic Prediction of Energy Proportions

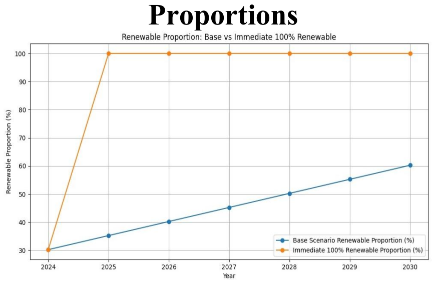

Figure 14. Renewable Proportion: Base vs Immediate 100%

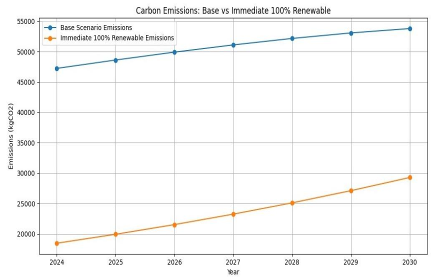

Figure 15. Carbon Emissions: Base vs. Immediate 100% Renewable

The emergency transformation scenario shows more radical change in the energy structures by simulating the possibility of 100% renewable energy supply in 2024. In this case, fossil fuel-related carbon emissions will be reduced to zero emissions from 2025. However, the operability of this scenario is limited by factors such as technology maturity, infrastructure expansion, and economic costs. From a long-term perspective, the immediate transformation scenario shows strong prospects in terms of environmental benefits and energy security. The sensitivity analysis of the model reveals that the growth rate of energy and the proportional growth rate of renewable energy have a significant impact on the behavior of the system. When the energy growth rate increases, the total energy consumption and carbon emissions of the system will increase. Conversely, when the annual growth rate of renewable energy is 17%, carbon emissions can be effectively controlled even under the high growth rate scenario. The result of sensitivity analyses is that promotes indirect increased energy growth and the development of renewable energy to reduce environmental costs.

2.5.3 Conclusion and Discussion

Through benchmarking and comparison of urgent transformation scenarios, the dynamic system model provides a clear quantitative picture of the energy conversion path and its consequences. Although the slow transformation is relatively stable, its environmental benefits are severely limited, indicating that the rapid transformation has great potential in terms of emission reduction, and the economic and technical requirements are higher. A comprehensive evaluation of the level of regional economic development, technical observation and social acceptance. Further research can improve the predictive power of the model, such as energy costs, technology maturity and social impact.

2.6 Game Theoretical Model for Operating Revenue and Water Efficiency

2.6.1 Methodology

Our study focuses on water-saving efficiency since Enhancing efficiency reduces energy demand for water treatment and distribution, cutting costs and emissions. Meanwhile its measurable impact on resource optimization and its ability to reveal the synergy between government policies and operator revenues.

In order to analyze the game-theoretical[9] relationship between operators and the government, the following methods are used in this study: First, the data is preprocessed, and a unified data set is constructed by combining operator revenue and government water-saving efficiency data [10]. Secondly, define the income function, which takes income and water-saving efficiency as variables and describes the synergy between the two. The formulae is given below:

$$Ic,y = Incomec,y \times Efficiencyc,y \quad (8)$$

The purpose of the income function is to highlight the gain effect of efficiency improvement on comprehensive income. Then, the income values of all countries and years are calculated based on the income function, and they are filled in a two-dimensional matrix to form a revenue matrix. The rows of the matrix represent the country, the columns represent the year, and the matrix elements are the income values of the corresponding country and year. Finally, heat map is used to analyze the distribution characteristics and dynamic changes of the income matrix, and to identify the income performance of various countries in different periods.

2.6.2 Data Processing and Revenue Calculation

First, the operator's revenue data and government water-saving efficiency data are merged to generate a joint data set with the year and country as the key fields. Based on the combined data, the income function is defined as the product of income and water- saving efficiency, reflecting the synergy between them. High income with low efficiency suppresses the comprehensive income value, while both being high maximizes it, capturing dynamic cooperative benefits. A revenue matrix [11] is then constructed by calculating and filling comprehensive income values for all countries and years into a two-dimensional matrix, with rows representing countries, columns representing years, and elements being the income values. Missing data is set to zero due to the lack of information for calculation.

The revenue matrix is displayed through the heat map, and the depth of the color represents the level of revenue value. This visualization method visually presents the income distribution and changing trends of various countries in different periods, and provides an important basis for the discussion of follow-up results.

2.6.3 Result and Discussion

Through calculation and analysis, significant differences in income values in different countries can be observed. Some countries have an advantage in operating income and water-saving efficiency, and their revenue value is generally higher. Although other countries have lower incomes, their high water-saving efficiency makes up for their disadvantages to a certain extent and shows strong competitiveness. In the time dimension, the income value of many countries has shown a steady growth trend, which may be related to policy adjustments or technological progress. At the same time, there are also some countries where income value fluctuates greatly in certain years, which may be affected by economic or environmental factors. As shown in Figure 16, the peaks in the revenue value in the revenue matrix are mainly concentrated in countries and years with high operating income and water-saving efficiency. This shows that based on optimizing resource allocation and improving efficiency, operators and governments can achieve win-win cooperation. On the contrary, for countries with low water-saving efficiency [12], even if their incomes are higher, their income value is still significantly restricted, which reflects the importance of efficiency improvement to optimize overall benefits.

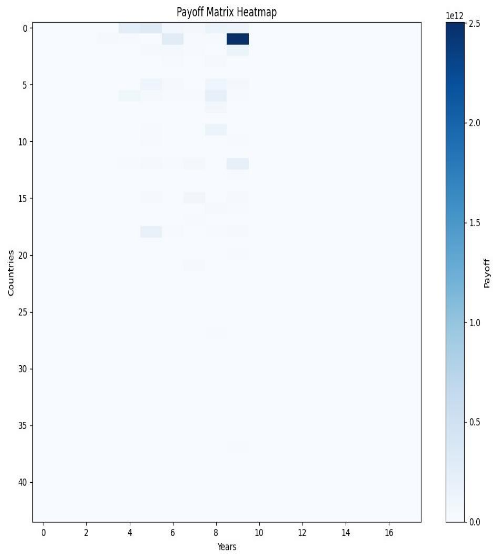

Figure 16. Payoff Matrix Heat map

3. Suggestion and Model Evaluation

3.1 Suggestion

Taking these findings together, we can suggest the following recommendations:

• First, technological progress and energy efficiency should be reinforced, especially in medium and high growth rates, to reduce the increase in carbon emissions;

• Second, we should diversify more towards low -carbon energy sources and reduce the reliance on high-carbon sources;

• Lastly, the government can take appropriate measures to promote the creation and use of energy- efficient technologies, especially in the high-growth environment, to successfully manage carbon emissions.

• Optimize Utilization: Organizations should aim to optimize utilization without burdening resources, achieving a balance between utilization and over utilization.

3.2 Strengths

• Our model adopts an uncommon dynamic system model, which is practicable but unique way.

• Our method involves considering different kinds of energy resources, not only consider energy use, in order to separate different factors of energy use.

• We introduced different scenarios to predict the HPC carbon emission till 2030, which means if there are change in policy, the prediction can be well showed.

3.3 Weaknesses

• Since the model is newly developed, it still needs more testing in order to get the model's best performance.

• The data is not comprehensive. It only has data with a time span of ten years, which still have error.

• Because of the short time span, it cannot show a long-term trend of carbon emission.

4. Conclusion

This study systematically evaluated the energy consumption and environmental impact of high-performance computing (HPC) and proposed a multi model prediction framework. The core conclusion is as follows:

Based on the analysis of global HPC system full load energy consumption, it is found that major suppliers contribute significantly, and there are regional differences in energy consumption. By integrating energy consumption, energy structure, and emission factors, the global HPC carbon emissions from 2014 to 2023 are estimated, reflecting energy efficiency improvements and the transition to renewable energy. Based on the elastic network regression model (combined with L1/L2 regularization and multicollinearity correction), it is predicted that carbon emissions will increase by 17.4% in 2030 compared to 2023 (assuming HPC energy consumption will increase by 5% annually) to verify the potential for renewable energy emission reduction. The dynamic system model quantifies the long-term emission reduction effects of renewable energy, while the game theory model reveals the competition and cooperation mechanisms of water resources in data centers.

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