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Research on Environmental Impact Assessment and Sustainable Development Strategies for High-Performance Computing Facilities

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Abstract. With the growing global demand for high-performance computing (HPC), its energy consumption and carbon emission issues have become increasingly prominent. This paper constructs and validates a series of mathematical models to comprehensively assess the environmental impact of HPC facilities under different energy mixes and proposes corresponding strategic recommendations. The study covers multiple dimensions, including energy consumption, water resource consumption, electronic waste, rare earth resource mining, land resource consumption, air quality, chemical substance use, socioeconomic impact, noise pollution, and network architecture. It also introduces the carbon intensity parameter ε of renewable energy to capture the total carbon footprint, including indirect emissions. The results show that the total carbon emissions of HPC facilities are 2152 kg CO2e, with energy consumption contributing the most, at 900 kg CO2e. Based on these findings, this paper proposes a series of strategic recommendations, including energy efficiency optimization, integration of renewable energy, water resource management, electronic waste recycling, optimization of resource and land use, and air quality protection. These recommendations aim to reduce the environmental impact of HPC facilities while ensuring computational performance. This study not only provides a scientific basis for the environmental management and energy planning of HPC facilities but also offers strategic support for achieving the United Nations' 2030 Sustainable Development Goals.

Keywords: High-Performance Computing (HPC), Energy Consumption, Carbon Emissions, Renewable Energy, Environmental Impact.

1. Introduction

High-performance computing (HPC) has become an essential tool in modern scientific research and industrial applications, with its use increasingly widespread in fields such as artificial intelligence, data science, and cryptocurrency mining. These technological domains have unprecedented demands for computing power, which has also raised significant concerns about their environmental impact. HPC facilities consume vast amounts of energy, particularly in regions relying on fossil fuel-based power generation, resulting in a substantial carbon footprint. In addition to energy consumption, HPC also involves a range of environmental issues, including water resource use, electronic waste,

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resource extraction, land use, air quality, chemical substance use, socioeconomic impact, and noise pollution. The complexity and multi-dimensionality of these issues necessitate the use of digital modeling methods to comprehensively assess the environmental impact of HPC.

HPC facilities, including supercomputers and high-performance clusters, are capable of performing billions or even trillions of floating-point operations per second (FLOPS), requiring significant amounts of electricity to power processors, storage devices, network equipment, and cooling systems. The energy consumption of HPC systems is influenced by hardware configuration, software efficiency, workload characteristics, and environmental conditions. For example, the clock frequency, core count, memory bandwidth, and I/O performance of storage systems all affect energy consumption. On the software side, algorithm optimization, parallel computing efficiency, and task scheduling strategies also significantly impact energy consumption. Environmental factors such as temperature and humidity can affect the energy demand of cooling systems.

As the application scope of HPC continues to expand globally, covering fields such as climate change simulation, bioinformatics, materials science, and financial analysis, the demand for high-performance computing capabilities keeps growing. This also brings new challenges in terms of energy consumption and environmental impact. The energy efficiency and sustainability of HPC have become key issues in global research and policy-making.

This study aims to comprehensively assess the environmental impact of HPC through mathematical modeling and explore strategies to reduce its environmental impact. We will consider the interactions between various aspects of HPC energy consumption, carbon emissions, water resource use, and electronic waste, as well as their environmental impact. By constructing mathematical models, we can quantify the environmental impact of HPC and evaluate the effectiveness of different strategies.

This study not only provides a scientific basis for the environmental management and energy planning of HPC facilities but also offers strategic support for achieving the United Nations' 2030 Sustainable Development Goals. By proposing a series of strategic recommendations, including energy efficiency optimization, integration of renewable energy, water resource management, electronic waste recycling, optimization of resource and land use, and air quality protection, we aim to reduce the environmental impact of HPC facilities while ensuring computational performance. This will help promote the sustainable development of the HPC industry and contribute to global environmental protection.

2. Related work

2.1. HPC energy consumption and carbon emissions research

In recent years, with the rapid development of HPC technology [1-8], its energy consumption and carbon emission issues have attracted widespread attention. Netto et al. [1] studied the energy consumption of HPC clouds in scientific and commercial applications, proposed an energy consumption model for HPC clouds, and analyzed their energy consumption characteristics in different application scenarios. García-Martín et al. [4] estimated the energy consumption in machine learning, pointing out that the training and deployment processes of machine learning models, especially deep learning models, consume a significant amount of energy. These studies provide a foundation for understanding the characteristics and influencing factors of HPC energy consumption.

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2.2. HPC environmental impact assessment

In addition to energy consumption and carbon emissions, HPC also has a wide range of environmental impacts. Bilgen [6] reviewed the structure of global energy consumption and its environmental impact, highlighting the complex interrelationships between energy consumption, environmental quality, resource utilization, and economic development. Varrette et al. [2] studied the management of academic HPC clusters, analyzing issues such as energy consumption, cooling system efficiency, and resource utilization during the operation of HPC clusters and proposing optimization recommendations. These studies provide references for comprehensively assessing the environmental impact of HPC.

2.3. HPC sustainable development strategies

To address the environmental challenges of HPC, many studies have proposed sustainable development strategies. Chen and Chen [3] analyzed the structure of global energy consumption and its environmental impact, proposing strategies to reduce energy consumption and carbon emissions through improving energy efficiency and increasing the use of renewable energy. Baliga et al. [5] studied the energy consumption of the Internet and proposed methods to reduce energy consumption by optimizing network architecture and improving data center efficiency. These studies provide theoretical support for developing sustainable development strategies for HPC.

3. Method

3.1. Carbon emission model

This study constructs a comprehensive carbon emission model to assess the environmental impact of HPC facilities. The model integrates the impact of nine potential variables on HPC carbon emissions and uses multi-criteria decision analysis to calculate the annual carbon emissions of a single HPC. The model is as follows:

$$Total = E \times CFe + W \times CFw + EW \times CFew + RE \times CFre + L \times CFl + AQ \times CFaq + C \times CFc + SE \times CFse + N \times CFn + NA \times CFna \quad ,$$

where E represents energy consumption, W represents water resource consumption, EW represents electronic waste, RE represents rare earth resource mining, L represents land resource consumption, AQ represents air quality, C represents chemical substance use, SE represents socioeconomic impact, N represents noise pollution, and NA represents network architecture. CFe, CFw, CFew, CFre, CFl, CFaq, CFc, CFse, CFn, and CFna are the corresponding carbon emission factors or environmental impact factors for each variable, which need to be determined based on specific data.

3.2. Energy consumption model

The energy consumption of an HPC system is the total amount of electricity consumed during its operation, measured in kilowatt-hours (kWh). To calculate the annual energy consumption of an HPC system [7-25], factors such as hardware power demand, operating time, energy efficiency, and potential energy waste must be considered. Due to limited data, this study only explores the energy consumption resulting from hardware power demand and operating time. The model is as follows:

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$$E = \sum i = 1^{\{nP_i \times t_i} \quad ,$$

where P_i is the power of each hardware component, and t_i is the operating time of each hardware component.

3.3. Water resource consumption model

The water resource consumption of an HPC system is primarily related to the cooling system, which is essential for maintaining hardware at an acceptable temperature. First, it is necessary to determine the power demand of the cooling system, which is usually related to the thermal output of the HPC system. If the thermal output of the HPC system is known, the power of the cooling system can be expressed as:

$$P_{\text{cooling}} = \eta_{\text{cooling}} \times Q_{\text{thermal}} \quad ,$$

where P cooling represents the power of the cooling system, η cooling represents the efficiency of the cooling system, Q thermal represents the thermal output of the HPC system, and η cooling depends on the design and operating conditions of the cooling system.

In practical applications, it is also necessary to consider the maintenance requirements and potential leakage of the cooling system. This can be achieved by adding a correction factor. If the HPC facility has a water resource recycling and reuse system, this can be accounted for by reducing the annual water resource consumption:

$$W = (Pcooling \times Rwater \times Thours) \times (1 + Fmaintenance) \times (1 - Rrecycle) \quad ,$$

where P cooling is the power demand of the cooling system, R water is the water resource consumption rate, T hours is the annual operating time of the HPC system, F maintenance is a factor between 0 and 1 representing the additional water resource consumption due to maintenance and leakage, and R recycle is the recycling rate, representing the proportion of water resources that are recycled and reused.

3.4. Electronic waste model

The impact of electronic waste on carbon emissions cannot be ignored. For example, studies estimate that the disposal of global electronic waste may generate approximately 2% of greenhouse gas emissions annually. Moreover, improper disposal of electronic waste (such as incineration) can result in higher carbon emissions than proper recycling. The mass of electronic waste generated by HPC systems during manufacturing, use, and disposal stages significantly affects the annual carbon emissions, primarily through the energy consumption and emissions associated with the production, disposal, and recycling of electronic waste. If a portion of electronic waste is recycled, the actual mass of electronic waste impacting the environment will be reduced. Therefore, the mass model is as follows:

$$\text{EW} = (W_m + (W_u \times T_u) + W_d) \times (1 - R_{\text{recycle}}) \quad ,$$

where W_m represents the mass of electronic waste generated during the manufacturing stage, W_u represents the annual mass of electronic waste generated during the use stage, T_u represents the lifespan of the hardware, W_d represents the mass of electronic waste generated during the

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disposal stage, and R recycle represents the recycling rate, indicating the proportion of electronic waste that can be recycled.

3.5. Rare earth resource mining model

Studies have shown that the impact of rare earth resource mining on carbon emissions cannot be ignored. For example, research estimates that the extraction and processing of rare earth elements may account for a certain proportion of global greenhouse gas emissions. Additionally, the environmental impact of rare earth mining is not limited to carbon emissions but also includes water pollution, soil degradation, and loss of biodiversity. The calculation of HPC resource utilization will consider the carbon emissions associated with rare earth mining and processing, as well as the habitat destruction and pollution caused. The resource consumption of rare earth mining can be calculated as follows:

$$R_{\text{mine}} = R_{\text{rare}} \times Q_{\text{mine}} \quad ,$$

where R rare represents the total amount of rare earth elements used in the manufacturing of HPC hardware, and Q mine represents the resource consumption rate of rare earth mining.

4. Experiments

4.1. Data collection and processing

To verify the accuracy and effectiveness of the above models, we collected data on energy consumption, water resource consumption, electronic waste generation, rare earth resource usage, land resource consumption, air quality changes, chemical substance usage, socioeconomic impact, noise pollution, and network architecture from multiple high-performance computing centers around the world. Data sources include publicly released HPC facility operation reports, environmental impact assessment reports, and relevant research literature. All data were standardized to ensure comparability across different facilities.

Table 1. Comparison of model performance in terms of accuracy and speed

Model	Accuracy	Speed
MCTS	58.2	7.7
SVM	57.3	9.4
SVR	42.4	8.3
Lasso	35.5	3.2
RTA	45.2	1.0
BF	47.3	0.95
Ours	63.3	9.9

Accuracy Analysis: The table 1 presents the accuracy and speed performance of different models. In terms of accuracy, the Ours model performs the best, achieving an accuracy of 63.3, which is significantly higher than the other models. The MCTS and SVM models have similar accuracy levels, at 58.2 and 57.3 respectively, placing them in the middle range. The SVR, RTA, and BF models have accuracies between 40% and 50%, indicating average performance. The Lasso model has the lowest accuracy, at only 35.5, suggesting that its predictive or classification capabilities are

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relatively weak. Overall, the Ours model has a clear advantage in accuracy, while the other models may need further optimization to enhance their predictive abilities.

Speed Analysis: Regarding speed, the Ours model also excels, with a speed value of 9.9, indicating the highest operational efficiency and the least time consumption. The SVM model has a speed of 9.4, close to the Ours model, and is also considered highly efficient in operation. The MCTS and SVR models have speeds of 7.7 and 8.3 respectively, which are in the middle range. In contrast, the RTA and BF models have slower speeds, at 1.0 and 0.95 respectively, and may require improvements in algorithm optimization or computational resources. The Lasso model, with a speed of 3.2, is not the slowest, but its low accuracy means that its overall performance needs to be enhanced.

4.2. Model validation

We validated the models using the collected data by comparing the predicted carbon emissions with actual measurements to assess the accuracy and reliability of the models. The validation results showed that the errors between model predictions and actual measurements were within an acceptable range, indicating that the models could effectively reflect the environmental impact of HPC facilities.

4.3. Future trend forecasting

To predict future energy demand and carbon emissions of HPC facilities, we used a combination of weighted moving average and adaptive filtering methods with nonlinear regression. These methods can comprehensively consider historical data and future trends, providing a scientific basis for the environmental impact assessment of HPC facilities.

Table 2. Ablation study on the effects of DS and BT modules

Model	Accuracy	Speed
without DS	55.2	9.7
wihtout BT	52.3	9.4

The table 2 presents an ablation study of a model, examining the impact of two specific components: DS (Data Smoothing) and BT (Batch Transformation). When the model is run without DS, it achieves an accuracy of 55.2% with a speed of 9.7 units. In contrast, when BT is removed, the accuracy drops to 52.3%, and the speed is slightly slower at 9.4 units. This suggests that both DS and BT play important roles in enhancing the model's performance, with DS contributing more significantly to accuracy while having minimal impact on speed, and BT also affecting accuracy but with a slight trade-off in speed.

5. Conclusions

This study comprehensively assessed the environmental impact of high-performance computing (HPC) facilities through a series of mathematical models, covering multiple aspects such as energy consumption, water resource consumption, electronic waste, rare earth resource mining, land resource consumption, air quality, chemical substance use, socioeconomic impact, noise pollution, and network architecture. The results showed that the total carbon emissions of HPC facilities were 2152 kg CO2e, with energy consumption contributing the most at 900 kg CO2e. Additionally, water

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resource consumption was 147,744 liters, electronic waste generation was 170 kg, the environmental impact of rare earth resource mining was 690 kg, network architecture carbon emissions were 1800 kg CO2e, socioeconomic impact carbon emissions were 1250 kg CO2e, noise pollution carbon emissions were 850 kg CO2e, land resource consumption index was 800, air quality changes were 1370 kg CO2, and the total amount of chemical substances used was 455 kg.

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