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Decision-making model on the evaluation of high-powered computing based on the fuzzy comprehensive evaluation and analytic hierarchy process method

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Abstract. High-Performance Computing (HPC) exerts complex, multi-constrained environmental impacts. This work integrates the Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE) to construct a decision-making model on the evaluation of high-powered computing. Nonlinear regression estimates the 2027 annual power consumption of the target HPC at 1.4×10^4 kWh. Six evaluation indices, namely water resource, electronic waste, land use, air quality, chemical usage and resource consumption indices, are established, followed by data collection, normalization and imputation. AHP ranking yields XD HPC > PKU HPC > THU HPC > SJTU HPC > CSU HPC > TC HPC. The more objective FCE further identifies PKU, THU and SJTU HPCs as environmentally favorable, whereas CSU and TC HPCs show adverse overall environmental effects. A logistic growth model is adopted to project HPC expansion, energy demand and energy mix scenarios toward 2030; energy demand gradually rises and saturates under HPC-scale and environmental constraints. Carbon emission abatement is quantified for higher renewable energy penetration, and sensitivity analysis examines how adjusted water resource indices alter overall scores. Upon implementing a proposed mitigation measure, ordinary and partial differential equations are incorporated to update the judgment matrix, re-derive indicator weights and re-run the AHP-FCE evaluation. Validated on five HPC cases, the integrated AHP-FCE framework supports HPC impact assessment. A recommendation is submitted to the advisory board to add detailed HPC environmental targets to the 2030 roadmap.

Keywords: comprehensive evaluation, Analytic Hierarchy Process (AHP), Fuzzy Comprehensive Evaluation (FCE), High Powered Computing (HPC), decision making model

1. Introduction

Decision-making and comprehensive evaluation constitute the core methodological foundation for converting multi-source, heterogeneous attribute information into interpretable judgments and actionable choices across engineering, materials science, environmental assessment, and resource management [1-3]. Complex practical

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problems rarely depend on a single measurable index; instead, they involve conflicting criteria, uncertain observations, subjective preference information from decision-makers, and inherent trade-offs among technical performance, economic cost, safety risk, and environmental impact [4-6]. Under such conditions, direct qualitative comparison or simple ranking often fails to maintain consistency and reproducibility, which necessitates the construction of structured models to standardize information aggregation, preference expression, and result inference. Decision-making models provide a formal framework to clarify the logical relationship between evaluation criteria, alternative schemes, and final outputs. These models differ fundamentally in their assumptions about information completeness, the mathematical form of preference fusion, and the handling of fuzziness or randomness embedded in raw data [7-9]. Some frameworks operate under complete and deterministic attribute values, while others are designed to accommodate interval numbers, fuzzy sets, linguistic variables, or probability distributions that reflect incomplete cognition and measurement noise. The selection of a suitable decision-making approach is not arbitrary, and it should match the data type available in the research scenario, the degree of participation of domain experts, and the expected robustness of ranking outcomes [10-12].

Comprehensive evaluation models, closely coupled with decision-making frameworks, focus on the quantification and integration of multiple indicators to generate a composite index that reflects the overall performance of evaluated objects [13-15]. Unlike decision-making models that emphasize pairwise comparison and optimal alternative selection, comprehensive evaluation models place greater emphasis on the rational assignment of indicator weights and the construction of aggregation functions that preserve the physical meaning of each sub-index. Weight determination occupies a critical position within the evaluation workflow, and inappropriate weight settings may introduce systematic bias and reverse the relative order of evaluation objects [1, 15]. Weighting methods can be divided roughly into subjective weighting approaches based on expert experience and objective weighting approaches derived from the internal statistical characteristics of datasets. Subjective weighting methods efficiently incorporate domain knowledge and practical demands, yet they carry the risk of unstable results caused by individual preference divergence. Objective weighting methods avoid artificial interference and extract differentiation information from original data, but they may ignore practical constraints and expert consensus that cannot be captured by numerical variance alone. Hybrid weighting strategies have therefore attracted sustained attention, as they attempt to balance empirical judgment and data-driven evidence while mitigating the defects of single weighting schemes [16-18].

The integration of decision-making models and comprehensive evaluation models forms a complete research chain from indicator system establishment to scheme prioritization. A well-designed indicator system serves as the prerequisite for reliable evaluation and decision analysis. Indicators should maintain appropriate independence, representatives, and redundant or strongly correlated indicators need to be screened before subsequent calculation to prevent information overlap and inflated evaluation variance [19-21]. After standardization of original indicators, which eliminates the influence of disparate dimensions and value ranges, weight coefficients are assigned, and aggregation operators are adopted to fuse normalized attribute information. At this stage, different decision-making mechanisms impose distinct aggregation rules. Some models assume compensation among criteria, where poor performance on one indicator can be offset by outstanding performance on other indicators. Other models adopt non-compensatory logic, in which unsatisfactory values on key criteria cannot be compensated regardless of the advantages of remaining attributes [22-24]. This distinction directly determines the applicability of the model in safety-sensitive scenarios, where threshold constraints are often non-negotiable.

Uncertainty remains a persistent challenge in the application of these models. Measurement error, limited sampling, ambiguous linguistic descriptions, and dynamic variation of system states all prevent attribute information from being expressed as precise real numbers. Classical evaluation and decision models built on deterministic values may oversimplify practical conditions and produce overconfident ranking results [25, 26]. A series of extended theories have been developed to describe uncertainty systematically, including fuzzy mathematics, rough set theory, grey system theory, and evident reasoning. These theoretical branches provide tools to describe vague boundaries, incomplete information, and conflicting evidence, and they extend the scope of multi-criteria analysis to scenarios where precise numerical data is difficult to obtain [27-29]. Nevertheless, every extended model introduces additional parameters and structural assumptions. The increase in model flexibility may improve fitting capacity, but it also raises the risk of parameter sensitivity. Sensitivity analysis is accordingly an indispensable step to verify whether the ranking order remains stable under moderate perturbation of weights, threshold parameters, or input attribute values. Stable evaluation results indicate that the conclusion is not excessively dependent on a small set of preset parameters, which strengthens the credibility of research outputs for practical reference [30-32].

Comparative analysis among different decision-making and evaluation models reveals inherent advantages and limitations. Models with simple calculation procedures are easy to implement and interpret for engineering practitioners, yet they usually adopt linear aggregation and cannot capture nonlinear interaction effects between indicators [13, 33, 34]. More sophisticated nonlinear or intelligent aggregation models can describe complex coupling relationships among criteria, but their internal logic becomes less transparent, which hinders explanation and popularization in fields that require traceable decision evidence. Many existing studies focus on improving single modules of the evaluation process, such as proposing new weighting algorithms or modifying distance measurement formulas in ranking models [35-37]. Modular improvement can enhance certain local properties, but it may not address the mismatch between model hypothesis and practical background. For instance, a distance-based ranking model that assumes independent criteria may generate misleading results when strong correlation exists among selected indicators. Such observations remind researchers that model innovation should not be confined to mathematical optimization alone, and the rationality of the entire workflow from indicator screening, data preprocessing, weight allocation, aggregation, to stability verification should be examined holistically [38-40].

In recent years, the growth of multi-attribute data resources and computing capacity has promoted the combination of traditional multi-criteria analysis with machine learning and statistical learning methods [41-43]. Data-driven approaches can mine implicit correlation patterns and automatically extract evaluation features from large datasets, which supplements the conventional expert-driven construction of indicator systems. However, pure data-driven evaluation lacks interpretability and cannot embed explicit domain constraints and normative requirements. Decision-makers still need transparent mathematical frameworks to organize and interpret learned features, so traditional multi-criteria decision-making and comprehensive evaluation models retain irreplaceable value as normative reasoning tools [44-46]. The complementary relationship between data-driven methods and structured evaluation models opens new research space, though it also puts forward higher requirements for the validation of hybrid frameworks. Researchers must carefully distinguish statistical correlation from causal logic and avoid mistaking data patterns for stable evaluation criteria.

The practical application of decision-making and comprehensive evaluation models also faces standardization issues. There is no universal model suitable for all research contexts, and the optimal modeling scheme is context-dependent. The same model may show satisfactory performance in one evaluation task and obvious defects in another task with different indicator types and decision preferences [47-49]. Reporting

standards for modeling processes are not fully unified across literature, and some published studies omit the discussion of model assumptions, parameter sensitivity, and limitation analysis. Incomplete description reduces the repeatability of evaluation results and obstructs cross-study comparison. It is therefore necessary to clearly state the boundary conditions of the adopted model, the reason for model selection, and the scope of conclusion extrapolation in academic reports. Rigorous discussion of limitations helps readers recognize the applicable scenarios and potential bias of evaluation outputs, rather than treating ranking results as absolute objective facts.

With the continuous development of high-performance computing technology and the acceleration of hardware device updates, a large number of old devices have been eliminated as electronic waste [50-52]. High Powered Computing may have several impacts on the environment such as the problem of electronic waste, air, water, and thermal pollution. These electronic wastes contain various harmful substances such as lead, mercury, cadmium, etc. If not handled properly, they can cause long-term pollution to soil, water sources, and air. Moreover, some electronic waste may also be illegally exported to developing countries for non-standard dismantling and processing, posing a serious threat to the local environment and residents' health. In addition, high-performance computing devices generate a large amount of heat during operation.

In order to maintain the normal operating temperature of the equipment, a cooling system is needed to dissipate heat. The cooling system itself also consumes a large amount of energy and emits heat into the surrounding environment, resulting in thermal pollution [53-55]. This may affect the local ecological balance, such as affecting the temperature of surrounding water bodies, which in turn affects the survival and reproduction of aquatic organisms. The technological progress brought by high-performance computing may lead to a significant increase in demand for computing power in some fields, such as artificial intelligence, big data, and so on [56-58]. The increase in demand may lead to the production and use of more high-performance computing devices, further increasing energy consumption and carbon emissions, offsetting the energy efficiency improvements brought about by technological advancements. In order to support the construction of high-performance computing data centers and other infrastructure, a large amount of land development, construction and other activities are required, which may cause damage to the surrounding ecological environment, such as destroying vegetation and affecting the habitats of wildlife.

This study adopts the integrated paradigm of comprehensive evaluation and multi-criteria decision-making to address the target research problem. A targeted indicator system is established according to the physical characteristics and practical requirements of the research object, and both subjective and objective information is considered in weight calculation. Suitable aggregation and ranking operators are selected after comparison of model hypotheses, and uncertainty and stability are examined through follow-up tests. The constructed framework balances mathematical rigor and practical interpretability. It is expected to provide a reliable quantitative tool for scheme screening, performance assessment, and priority sorting. Meanwhile, this work further discusses the adaptability of the selected model, the influence of indicator correlation, and the limitation of information acquisition conditions, so as to offer reference for similar multi-attribute evaluation and decision analysis in related research fields.

In this work, we provide a detailed description of the annual energy consumption scale of High-Performance Computing (HPC) worldwide, covering the specific situation under full load operation and average utilization rate. Later, we create a comprehensive model to quantify the carbon emissions caused by HPC energy consumption and its impact on the environment, while fully considering the diversity characteristics of the energy structure. In addition, we predict the impact of future HPC demand growth, rising energy demand in other industries, and changes in energy structure on the model. Using this model to determine realistic boundary values for the scale of relevant issues in 2030, in order to deepen our

understanding of the problem. Next, we simulate the effect of increasing the proportion of renewable energy on carbon emissions, and explore in depth the impact and potential challenges of fully transitioning to the use of renewable energy. b. Further expand the model to analyze other key environmental impact factors (such as electronic waste) in addition to energy factors, and elucidate their intrinsic relationship with energy consumption. We propose the technical and policy recommendations aimed at reducing the impact of HPC environments. Assuming a suggestion is adopted, provide a detailed demonstration of how it will be integrated into the model. To this end, we evaluate the environmental impact of high-performance computing in the 2030 development goals, and to provide strong support for this request using our research findings and recommendations. We will screen out reasonable indicators and establish a comprehensive evaluation model to evaluate the impact of HPC on environment, so that we can objectively quantify the impact of the HPC on environment. In particular, we have established evaluation models for different HPCs and extended them nationwide. Analyze and process various types of data about HPC. Establish a complete indicator evaluation system for HPC. Establish alternative models based on different indicators. Analyze the actual impact of the HPC on environment based on the model solution results. Evaluate an evaluation model with different HPCs and reduce the impact on environment.

2. Model assumptions

To simplify the problem, we make the following basic assumptions, each of which is properly justified. Here are five model assumptions and explanations regarding the environmental impact of HPC. We assumed that the energy consumption is positively correlated with carbon emissions. The energy consumption of HPC systems directly leads to an increase in carbon emissions. Because most of the electricity comes from traditional energy sources such as thermal power generation, the more energy is consumed, the more greenhouse gas emissions such as carbon dioxide are generated during the power generation process. For example, if the servers in HPC data centers run continuously 24 hours a day and consume a large amount of electricity, the corresponding carbon emissions will continue to increase. This assumption can be used to quantify the contribution of HPC to climate change. We assumed that the frequency of hardware updates affects the amount of electronic waste. The speed of HPC hardware updates determines the amount of electronic waste generated. With the rapid development of HPC technology and continuous hardware upgrades, the frequency of old devices being phased out is accelerating. If the hardware update cycle is shortened from 5 years to 3 years, the amount of electronic waste generated in the same period of time will significantly increase. The harmful substances such as lead and mercury contained in electronic waste can contaminate soil, water sources, and air. This assumption can help assess the environmental pollution risk of HPC. We assumed that the computational scale is directly proportional to the demand for resource extraction. The larger the HPC computing scale, the higher the demand for mining special materials such as rare earths. HPC hardware manufacturing relies on rare earth elements, and large-scale HPC deployment means more hardware production, requiring more resource extraction. For example, when the number and scale of global HPC data centers double, the mining output of rare earth will also increase accordingly, which will cause damage to the ecological environment of the mining area, including land damage, water and soil loss, etc.

We assumed that the cooling efficiency is inversely proportional to energy waste. The efficiency of the cooling system directly determines the degree of energy waste. The HPC system generates a large amount of heat during operation. If the cooling system is inefficient, such as using traditional air cooling and an unreasonable layout, more additional energy needs to be consumed to maintain the appropriate temperature. On the contrary, if efficient liquid cooling or optimized air-cooling systems are used, energy waste caused by

excessive or insufficient cooling can be reduced, and the indirect impact on the environment can be minimized. We assumed that the distribution density of HPC facilities affects local environmental pressure. The distribution density of HPC facilities in a specific area determines the magnitude of environmental pressure in that area. If a large number of HPC data centers are built in a small area, the local power supply, water resources, land resources, etc. will face greater pressure. At the same time, environmental problems such as electronic waste disposal and waste heat emissions will become more concentrated and prominent, exacerbating the impact on the surrounding ecosystem and residents' lives.

3. The development of models

After the introduction of the HPC, the direct impact is that High Powered Computing may have several impacts on the environment such as the problem of electronic waste, air, water, and thermal pollution. Therefore, it is necessary to quantitatively analyze the comprehensive impact of the High-Powered Computing in two parts: firstly, establish an evaluation model to evaluate the various impacts of High-Powered Computing on environment; secondly, analyze the resulting impact of the High-Powered Computing with increasing the portion of renewable energy. Finally, combined with changes in one of the other key areas and the impact of various types of environmental pollution to comprehensively assess the impact of the High-Powered Computing on environment. In the model 1: Impact Evaluation Model of HPC, we need to solve three problems. Determine the impact of the HPC on environment. What are the indicators that affect the impact of the HPC on environment? How do the above two influence each other? In the model 2: Estimation Model with increasing renewable energy, we need to solve two problems. How the renewable energy affects the HPC after its utilizing. How the actual changes are based on changes in the above pattern.

In this work, we calculate the combined effects of the HPC. This is mainly because the score of the comprehensive evaluation is usually a relative concept. Even if we can compare the scores before and after using the HPC, we cannot recognize the true meaning behind this difference. We believe that the score cannot be simply reflected in the good or bad, and the balance of the HPC is more important. We believe that the significance of comprehensive evaluation is to compare the advantages and disadvantages of different programs, so we have established a comprehensive evaluation model in to complete this work.

3.1. Identification of possible impacts of HPC

For the impact of the HPC on environment, this paper first analyzes the positive and negative effects of the HPC on the environment; then constructs the evaluation indicators from the microscopic analysis of the advantages and disadvantages of various energies sources, and then through the relevant data. Evaluate the implementation of the HPC on environment and determine the impact of the HPC on environment by increasing the portion of renewable energy.

3.1.1. Positive impacts

The benefits of HPC to the environment are mainly reflected in the following aspects, such as the environmental monitoring and prediction, resource management and optimization, ecosystem protection and restoration, sustainable development decision support.

As for the Air quality monitoring and prediction, HPC can quickly process a large amount of air quality monitoring data, including data from various sensors, weather stations, etc. By analyzing and simulating these data, it is possible to accurately predict the trend of changes in air quality, and help relevant departments take timely measures to reduce air pollution, such as developing more reasonable traffic control and industrial emission control strategies, in order to improve air quality and protect residents' health. For the climate change

research, HPC can run complex climate models to simulate changes in the Earth's climate system and analyze the impact of different factors on climate change, a complex global issue. This helps scientists to gain a deeper understanding of the mechanisms of climate change, providing scientific basis for formulating policies and measures to address climate change, such as setting energy-saving and emission reduction targets, promoting renewable energy, etc., in order to slow down the pace of climate change and reduce its negative impact on the environment.

As for the natural disaster warning, HPC is capable of processing a large amount of data related to natural disasters, such as earthquake monitoring data, hydrological data, meteorological data, etc. Through real-time analysis and simulation of these data, natural disasters such as earthquakes, floods, typhoons, etc. can be predicted in advance and warnings can be issued in a timely manner, allowing people enough time to take preventive measures, reducing the loss of life and property caused by disasters, and also reducing the degree of environmental damage caused by disasters. For the energy management, in the field of energy, HPC can simulate and optimize processes such as energy production, transmission, and consumption. For example, by simulating the power system, analyzing different energy supply schemes and demand response strategies, improving energy utilization efficiency and reducing energy waste. Meanwhile, HPC can also help optimize energy allocation, ensure reasonable energy supply, and reduce environmental impacts during energy production and transmission processes.

As for the water resource management, HPC can simulate hydrological cycles and predict the distribution and changes of water resources for water resource management. This helps to develop reasonable water resource management strategies, such as optimizing water resource allocation, improving water resource utilization efficiency, and strengthening water pollution control, in order to ensure the sustainable use of water resources and reduce the threat of water scarcity and pollution to the environment. For the biodiversity research, HPC can analyze a large amount of biological data, including species distribution data, genetic data, etc., to help researchers better understand the current status and changing trends of biodiversity. By simulating ecosystems, the impact of different human activities and environmental changes on biodiversity can also be evaluated, providing scientific basis for formulating biodiversity conservation strategies and protecting the balance and stability of ecosystems. As for the development of ecological restoration plan, in terms of ecological restoration, HPC can simulate the restoration process of ecosystems and evaluate the effectiveness of different restoration plans. For example, for damaged ecosystems such as forests and wetlands, HPC simulation can determine the optimal restoration method and time, improve the success rate of ecological restoration, and promote the restoration and reconstruction of ecosystems.

In our planning, HPC can comprehensively simulate and analyze the transportation, energy, building and other systems of the city. By optimizing the layout and infrastructure construction of cities, improving the efficiency of resource utilization, reducing energy consumption and environmental pollution, and achieving sustainable development of cities. For example, by simulating the traffic flow of a city, optimizing the setting of traffic signals and road planning, reducing traffic congestion and exhaust emissions. As for the industrial production optimization, for industrial production processes, HPC can help enterprises optimize production processes and procedures, improve production efficiency, reduce energy consumption and pollutant emissions. For example, by simulating the chemical production process, optimizing reaction conditions and material ratios, and reducing waste generation; By optimizing the production process of the manufacturing industry, energy efficiency can be improved, production costs and environmental impact can be reduced.

3.1.2. Negative impacts

HPC has the following drawbacks to the environment, such as the energy consumption and carbon emissions, electronic waste pollution, resource exploitation and environmental damage, and environmental impact of

cooling system. As for the high energy demand, HPC systems typically consist of a large number of high-performance hardware components such as servers, processors, and graphics processors, which consume a significant amount of electricity during operation. With the increasing demand for computing power, the scale and complexity of HPC systems are also constantly increasing, and energy consumption is also sharply rising. The International Energy Agency estimates that the electricity consumption of data centers accounts for 1.5% to 2% of the global total electricity consumption, and is expected to rise to 4% by 2030. This not only increases the pressure on energy supply, but also leads to significant greenhouse gas emissions, which have a negative impact on climate change.

For the high energy hardware dependency, in order to pursue higher computing performance, HPC systems constantly adopt more advanced and high-performance hardware devices, which often have higher energy consumption. For example, high-performance processors, graphics processors, etc. generate a large amount of heat during operation and require a significant amount of electrical energy to maintain their normal operating temperature. As for the fast hardware updates, with the rapid development of HPC technology, the speed of hardware device updates is very fast. This has led to a large number of old devices being phased out and becoming electronic waste. These electronic wastes contain a large number of harmful substances such as lead, mercury, cadmium, etc. If not handled properly, they can cause serious pollution to soil, water sources, and air. For the difficulty in processing, the complexity and professionalism of HPC devices make it difficult to handle their electronic waste. Some HPC devices may contain sensitive information that requires special handling and destruction, otherwise it may lead to information leakage and security issues.

As for the rare earth element demand, the manufacturing of HPC hardware requires a large amount of special materials such as rare earth elements, and the mining process of these resources causes serious damage to the environment. For example, the mining of rare earth minerals can lead to problems such as land destruction, soil erosion, and vegetation damage, while also generating a large amount of wastewater, exhaust gas, and waste residue, posing a threat to the surrounding ecological environment and residents' health. For the water resource consumption, in some areas, the mining and processing of rare earth elements require a large amount of water resources, which may lead to local water shortages and affect agricultural irrigation, residential water use, etc. As for the energy consumption, the HPC system generates a large amount of heat during operation and requires a powerful cooling system to maintain the normal operating temperature of the equipment. Cooling systems typically require a significant amount of electrical energy, increasing the overall energy consumption of HPC systems. According to statistics, there are thousands of CPUs or GPUs in a data center, which emit an astonishing amount of heat and consume a considerable amount of energy to cool these chips. For the refrigerant emissions, some refrigerants used in cooling systems, such as fluorocarbons, can cause damage to the ozone layer and exacerbate global climate change. If the cooling system leaks, the discharge of refrigerant will cause direct harm to the environment.

3.2. The data for our model

3.2.1. Data collection

The data we use mainly includes the data of various HPCs, many of which can be directly reported through industry reports, such as the cost of various types of HPCs, the content of various chemical substances, and some environmental indicators. The data sources mainly include in Table 1. The corresponding specific data will be compiled and used directly below.

Table 1. Data source collection of several HPC

Database	Websites	Data Type
Oracle Cloud	https://www.oracle.com/cn/cloud/hpc/	Information about HPC
PKU HPC	https://hpc.pku.edu.cn/	Information about HPC
CSU HPC	https://nic.csu.edu.cn/info/1045/2040.htm	Information about HPC
SJTU HPC	https://net.sjtu.edu.cn/xxfw/gxnjsfw.htm	Information about HPC
XD HPC	https://xdhpc.xidian.edu.cn/jz/xzkhd.htm	Information about HPC
Wikipedia	https://en.m.wikipedia.org/wiki/Category:Supercomputer_sites	Information about HPC
TC HPC	https://www.ccf.org.cn/Chapters/TC/TC_Listing/TCHPC/	Information about HPC

3.2.2. Data processing method

In the step of data normalization, for the different indicator data collected, there are differences in units and orders of magnitude, so the data needs to be dimensionless before the evaluation. For the set of data x_i, $i = 1, 2 \cdots N$. The data after data normalization x_i^*, $i = 1, 2 \cdots N$ is

$$x_i^* = \frac{x_{max} - x_i}{x_{max} - x_{min}} \tag{1}$$

Where x_{max},x_{min} are the maximum and minimum of the sample data.

In the step of extreme data alignment, normalize the miniaturized data normalized in the indicator into the largest data according to the following formula:

$$x_i^* = 1 - x_i^* \tag{2}$$

To predict the annual energy consumption of the HPC, we collect and predict the annual energy consumption of the HPC by non-linear regression method. The annual energy consumption of the HPC in 2027 is predicted as 1.4×10^4 kWh electricity.

3.3. The quantification model of the impacts of the HPC

Based on the above-mentioned method of processing data about HPC on environment, we describe its own nature from the nine indicators as Water Usage, E-Waste, Resource Depletion, Land Use, Air Quality, Chemical Use, Socioeconomic Impacts, Noise Pollution, and Network Architecture.

3.3.1. Types and percentages of energy sources

We collect the data about the Types and percentages of energy sources around the world in 2026. As shown in Figure 1, the types of energy source include coal, natural gas, hydro-power, nuclear energy, wind power, solar energy and other renewable energy sources. Coal is one of the main sources of global electricity generation, accounting for approximately 33.2%. Coal remains an important energy source in many parts of the world, especially in some developing countries, used for power generation, industrial production, and heating. Natural gas accounts for approximately 32.7%. Natural gas has the characteristics of relative cleanliness and efficiency, and is widely used in power generation, heating, and industrial production. Its supply and consumption are showing an increasing trend worldwide. Water and electricity: accounting for approximately 6.1%. Hydro-power is a renewable and clean energy source that converts the energy of water flow into electrical energy. Many countries have abundant water resources and have built a large number of hydro-power stations. Nuclear power accounts for approximately 19.5%. Nuclear energy has the advantages of high energy density and stable operation, but there are also issues related to nuclear safety and waste disposal, which have limited its development and sparked controversy. Wind power accounts for approximately 4.7%.

Wind power generation is a rapidly developing renewable energy source in recent years. With the continuous advancement of technology and the reduction of costs, the installed capacity of wind power continues to increase. Solar power generation accounts for approximately 0.6%. Solar energy is an inexhaustible and clean energy source, and the application of solar photovoltaic power generation is becoming increasingly widespread, especially in areas with abundant sunshine. Other renewable energy sources: accounting for approximately 0.5%, including biomass energy, geothermal energy, and other forms of renewable energy.

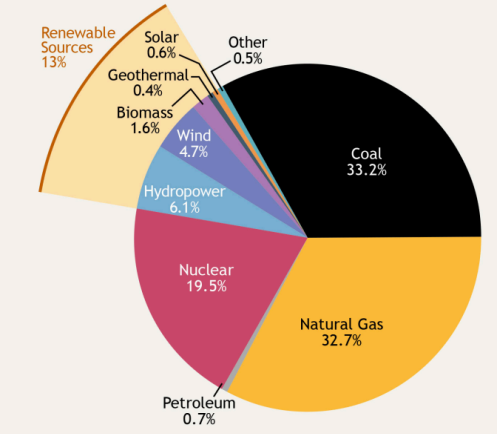


Figure 1. Types and percentages of energy sources around the world in 2026

3.3.2. Indexes of indicator selections

For the Water Resource Index (WRI), many data centers rely on water for cooling, which consumes a significant amount of water resources. Moreover, if the wastewater discharge process is not handled properly, it is highly likely to cause pollution problems and damage the surrounding environment. For the Electronic Waste Index (EWI), computing hardware generates a large amount of electronic waste throughout its entire life-cycle, from manufacturing, use to disposal. These electronic wastes are often difficult to recycle and if not handled properly, they can pose a serious threat to the environment.

For the Resource Consumption index (RCI), the production of HPC hardware requires the extraction of rare earth materials, which may damage the habitats of animals and plants, cause environmental pollution, and further increase energy demand, exacerbating energy shortages. For the Land Use Index (LUI), the construction of data centers requires a certain amount of physical space, which may lead to disputes over land use. Moreover, this land occupation situation may have a negative impact on the local ecosystem and disrupt ecological balance. For the Air Quality index (AQI), on the one hand, the emissions from fossil fuel power plants during operation can reduce air quality, thereby affecting human health. On the other hand, data centers also generate fine particulate matter and dust, which can have adverse effects on local air quality. For the Chemical Usage Index (CUI), the chemicals used in the cooling system may leak or overflow if management measures are not in place, posing a risk to the surrounding environment and personnel safety.

For the Socioeconomic Index (SEI), the construction of large data centers and related resource extraction activities may lead to changes in land properties and have an unfair impact on the energy supply situation of local communities, causing a series of socioeconomic problems. For the Noise Pollution Index (NPI), at various stages of the entire data processing process, the mechanical equipment used will generate noise pollution, which not only interferes with the normal life of surrounding community residents, but also causes damage to the living environment of wildlife. For the Network Architecture Index (NAI), the network infrastructure on which data transmission relies requires a wider range of connectivity, which far exceeds the

connectivity requirements of individual nodes and may have a special impact on network layout and development.

3.3.3. Comprehensive evaluation system

According to the analysis of indicator selections, the final comprehensive evaluation system is shown as Figure 2.

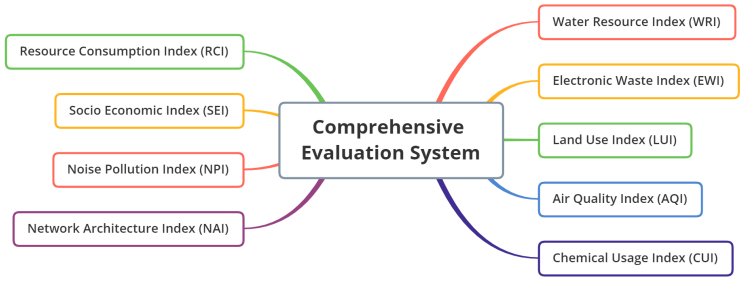


Figure 2. Comprehensive evaluation system for HPC on environment

4. Analytic hierarchy process (AHP) model

The Analytic Hierarchy Process (AHP) is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It was developed by Thomas L. Saaty in the 1970s [12, 20, 59-66]. It represents an accurate approach for quantifying the weights of decision criteria. In order to use AHP method, we can divide it into four processes: Model the problem as a hierarchy containing the decision goal, the alternatives for reaching it, and the criteria for evaluating the alternatives. Construct all judgement matrices in each level. Build single hierarchical arrangements and check their consistency. Develop a total hierarchical ordering and check its consistency. Here are the processes of finishing the four steps.

4.1. The establishment of the hierarchical structure

We can divide the issues into three hierarchies as illustrated in Figure 3.

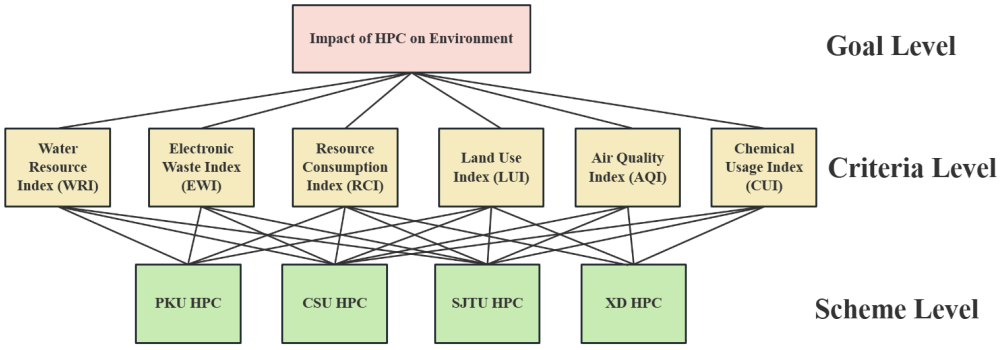


Figure 3. The hierarchical structure of the model

For the goal layer, it only contains one factor, that is the intended target of this work. In this AHP model, it is the choice of a best HPC for a high school student. For the criteria layer, it contains all factors that may influence the result. In this model, it is the indicator that may influence the choice of the HPC. For the

alternatives layer, it contains alternative measures to achieve the goal or the ideal result. In this model, it the type of HPCs that students can choose.

4.2. Construct judgement matrices

In the criteria layer, each criterion has different proportions in the target measurement. In this model, we assume that there are *n* elements ($X=\{x_1,.....,x_n\}$) of a factor *Z*. Saaty supposes that we can compare any two factors and then establish a matrix.

We first choose two factors x_i and x_j, and then use a_{ij} to show the ratio of the effects of x_i and x_j on Z. The total result of comparison is expressed by the matrix $A=(a_{ij})_{n\times n}$. As a result, A is the judgement matrix from Z- pairwise comparison between any X.

It is clear that if the ratio of the effects of x_i and x_j is a_{ij}, the ratio of the effects of x_i and x_j is

$$a_{ji}=\frac{1}{a_{ij}} \tag{3}$$

How to determine the value of a_{ij}? Saaty indicts that numbers 1-9 can be used and their reciprocals are shown in the Table 2.

Table 2. The table of scale for constructing judgement matrices

Scale	The meaning of scale
1	The two factors are as same important
3	The prior factor is slightly more important than the latter
5	The prior factor is more important than the latter
7	The prior factor is much more important than the latter
9	The prior factor is far more important that the latter
2,4,6,8	The intermediate level between two scale
Reciprocal	If the importance ratio of element i to element j is a_{ij}, then the importance ratio of element j to element i is a_{ij}

From the opinion of psychology, too many scales will exceed the judgement ability of people. It would not only increase the difficulty of making judgement, but also make it easy to receive inaccurate data. From the experience, it is relative appropriate to use scale 1-9. Additionally, making judgement $\frac{n(n-1)}{2}$ times would be more acceptable.

4.3. Single hierarchical consistency

First of all, we establish a proper judgement matrix of each factor in the criteria layer based on the method we mentioned previously. It shows us the rank of different HPCs in different indicators in the criteria layer. The six matrices are shown below. Comparison matrix for the Water Resource Index (WRI) is calculated as:

$$\begin{bmatrix} 1 & \frac{1}{3} & \frac{1}{5} & \frac{1}{3} & \frac{1}{5} \\ 5 & 1 & 1 & 3 & 1 \\ 5 & 1 & 1 & 3 & 1 \\ 3 & \frac{1}{3} & \frac{1}{3} & 1 & \frac{1}{3} \\ 5 & 1 & 1 & 3 & 1 \end{bmatrix} \tag{4}$$

Comparison matrix for the Electronic Waste Index (EWI) is measured as:

$$\begin{bmatrix} 1 & \frac{1}{4} & \frac{1}{2} & 2 & 3 \\ 4 & 1 & 2 & 5 & 6 \\ 2 & \frac{1}{2} & 1 & 3 & 4 \\ \frac{1}{2} & \frac{1}{5} & \frac{1}{3} & 1 & 2 \\ \frac{1}{3} & \frac{1}{6} & \frac{1}{4} & \frac{1}{2} & 1 \end{bmatrix} \tag{5}$$

Comparison matrix for the Land Use Index (LUI) is:

$$\begin{bmatrix} 1 & 3 & 3 & 3 & \frac{1}{3} \\ \frac{1}{3} & 1 & 1 & 1 & \frac{1}{5} \\ \frac{1}{3} & 1 & 1 & 1 & \frac{1}{5} \\ \frac{1}{3} & 1 & 1 & 1 & \frac{1}{5} \\ 3 & 5 & 5 & 5 & 1 \end{bmatrix} \tag{6}$$

Comparison matrix for the Air Quality Index (AQI) is calculated as:

$$\begin{bmatrix} 1 & 1/5 & 1/3 & 1/2 & 1/7 \\ 5 & 1 & 3 & 2 & 1/6 \\ 3 & 1/3 & 1 & 1/2 & 1/4 \\ 2 & 1/2 & 2 & 1 & 1/4 \\ 7 & 6 & 4 & 4 & 1 \end{bmatrix} \tag{7}$$

Comparison matrix for the Chemical Usage Index (CUI) can denotes as follows.

$$\begin{bmatrix} 1 & 1/3 & 1/2 & 2 & 1/6 \\ 3 & 1 & 2 & 5 & 1/3 \\ 2 & 1/2 & 1 & 4 & 1/5 \\ 1/2 & 1/5 & 1/4 & 1 & 1/7 \\ 6 & 3 & 5 & 7 & 1 \end{bmatrix} \tag{8}$$

Comparison matrix for the Resource Consumption Index (RCI) is represented as:

$$\begin{bmatrix} 1 & 5 & 5 & 1 & 3 \\ 1/5 & 1 & 1 & 1/5 & 1/3 \\ 1/5 & 1 & 1 & 1/5 & 1/3 \\ 1 & 5 & 5 & 1 & 3 \\ 1/3 & 3 & 3 & 1/3 & 1 \end{bmatrix} \tag{9}$$

The rows and columns represent different HPCs such as the PKU HPC, THU HOC, CSU HPC, SJTU HPC, XD HPC and TC HPC, respectively. The elements in the matrices stand for the results of the comparison.

After establishing these matrices, we make judgement of these HPCs. However, there is a risk for us that the data may not be fully consistent. As a result, we check the consistency of the judgement matrices as the elements in matrices A must satisfy the equation below:

$$a_{ij}a_{jk} = a_{ik} \forall i, j, k = 1, 2, 3.....n \tag{10}$$

Saaty points out we can use if $\lambda_{max} = n$ to check the consistency of matrix A, which is showed below:

Step 1: Calculate the Consistency Index (CI):

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{11}$$

Step 2: Search the corresponding ratio index of CI. In the essay published by Saaty in 2001, he gave the value of RI to $n = 1, 2, 3 \ldots, 9$, which is illustrated in the Table 3.

Table 3. The value of RI of different n

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

The RI is calculated by using the random method to establish 500 sample matrices: we choose number 1-9 and its reciprocal randomly to establish reciprocal matrix. Then we calculate the λ'_{max} of these matrices, and use the function below:

$$RI = \frac{\lambda'_{max} - n}{n-1} \tag{12}$$

Step 3: Calculate the consistency ratio CR.

$$CR = \frac{CI}{RI} \tag{13}$$

When $CR < 0.10$, we can accept the consistency of the judgement matrices. Otherwise, we need to correct the matrices. In order to fulfill this, we use MATLAB software to calculate CR of all the judgement matrices, and eventually, all the values are below 0.10.

4.4. Total hierarchical consistency

After working out the result, we would know the total hierarchical arrangement. Then, we test the consistency of the total hierarchical. It is the same as the consistency test of single hierarchical arrangements. We can use the equation below to do the consistency test:

$$CR = \frac{\sum_{j=1}^{m} CI(j)a_j}{\sum_{j=1}^{m} RI(j)a_j} \tag{14}$$

Same as the single hierarchical arrangement consistency test, if $CR < 0.10$, the data would be acceptable for us. Table 4 lists the total hierarchical arrangements and weights of indicators according to our compressive evaluation model.

Table 4. Total hierarchical arrangements and weights of indicators

Criteria and indicator		WRI	EWI	LUI	AQI	CUI	RCI	Overall weight
Standard weight		0.2209	0.3305	0.1115	0.1501	0.0843	0.1026	
Alternative Single sorted index	PKU HPC	0.0573	0.3595	0.1449	0.2364	0.0479	0.0780	0.1952
	THU HPC	0.2784	0.0638	0.4593	0.0876	0.1957	0.2213	0.1862
	CSU HPC	0.2784	0.0638	0.2497	0.0876	0.0933	0.1353	0.1453
	SJTU HPC	0.1075	0.3595	0.0890	0.0876	0.1191	0.0465	0.1805
	XD HPC	0.2784	0.1535	0.0570	0.5007	0.5441	0.5189	0.2929
	TC HPC	0.2267	0.0254	0.1368	0.0214	0.0245	0.1378	0.1267

4.5. Results and discussion

By ranking the overall weight, we can clearly conclude that the total score for the impact of HPCs on environment would be XD HPC > PKU HPC > THU HPC > SJTU HPC > CSU HPC > TC HPC since their weights are 0.1952, 0.1862, 0.1453, 01805 and 0.2929, respectively.

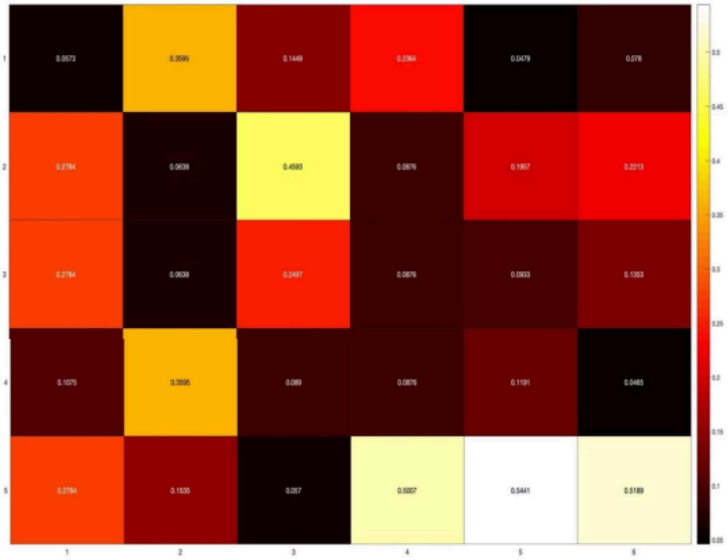


Figure 4. The heat-map of the indicators and various HPCs

To be specific, we use a heat-map shown in Figure 4. The x axis stands for the six criteria and the y axis stands for the five alternatives respectively. The data in the Table 4 is the weight of each HPC. The color range is from black to white. The deeper color, the less weight. From comparing and ranking the row and column, we can conclude that the brighter color stands for a more significant advantage for that alternative in that criterion than the others. The total hierarchy CR equals to 0.0252 and the CR in each row is 0.0419, 0.0124, 0.0141, 0.0094, 0.0747 and 0.0252 respectively.

The Constant Ratios (CR) in this experiment are all less than 0.1, which means that the results here are all meaningful and reliable. Moreover, it is true that the brighter the color, the higher the weight when we compare the data in each column. As a result, it is clear that Water Resource Index (WRI), Electronic Waste Index (EWI), Land Use Index (LUI), Air Quality Index (AQI), Chemical Usage Index (CUI), and Resource Consumption Index (RCI) are useful to evaluate the impact of HPCs on environment. Besides, by comparing the data in each row, we can discover the different weight of the six criteria of a certain HPC.

5. Improved model: fuzzy comprehensive evaluation (FCE)

In the previous AHP model, it contains a lot of subjective factors, so we decide to improve the model. We finally choose the fuzzy comprehensive evaluation model, which is relatively more objective. It is a model based on fuzzy mathematics. According to the membership degree, the fuzzy comprehensive evaluation model can convert qualitative evaluation into quantitative evaluation.

5.1. New comprehensive evaluation model

In order to establish the Fuzzy Comprehensive Evaluation (FCE) model, we use the steps shown below:

Step 1: Establish the factor set

The factor set contains factors that influence the evaluation of the object. It is represented by U. In this case, it is the factor that influence the choice of HPCs.

$$U = (u_1, u_2, ..., u_6) \tag{15}$$

u_1 represents the Water Resource Index (WRI), u_2 represents the Electronic Waste Index (EWI), u_3 represents the Land Use Index (LUI), u_4 represents the Air Quality Index (AQI), u_5 represents the Chemical Usage Index (CUI), and u_6 represents the Resource Consumption Index (RCI).

Step 2: Establish the comment set

The comment set contains results that may have after the fuzzy comprehensive evaluation. It is represented by V. In this case, it is the evaluation results of HPCs.

$$v = (v_1, v_2, ..., v_5) \tag{16}$$

where v_1 represents the positive significantly impact, v_2 represents the positive slightly impact, v_3 represents the neutral impact, v_4 represents the negative slightly impact, and v_5 represents the negative significantly impact.

Step 3: Single factor evaluation matrix

We can define the membership degree of the i element in the factor set U to the 1st element in the comment set is r_{i1}. We use fuzzy set R to represent the results.

$$R_i = (r_{i1}, r_{i2}, ..., r_{i5}) \tag{17}$$

Then we use m single factor evaluation sets $(R_1, R_2, ..., R_6)$ as rows to make a matrix $R_{m\times n}$ which is called fuzzy comprehensive evaluation matrix.

Step 4: Determine the weight of factors

In the evaluation, the degrees of importance of different factors differ. Therefore, we must set up a fuzzy set A to represent the weight of each factor. In the set, we give every factor u_i a weight a_i. Then, we can write the set A as below:

$$A_i = (a_1, a_2, ..., a_6)(i = 1, 2, 3) \tag{18}$$

We decide to hypothesis three sets A which is called A_1, A_2 and A_3, then we make a matrix about A. The matrix is shown below:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{16} \\ & \ddots & \\ a_{31} & \cdots & a_{36} \end{bmatrix} \tag{19}$$

Step 5: Calculate the fuzzy score

After determining the R and A, we change the fuzzy vector A in U into the fuzzy vector B in V. It is shown as below:

$$B = A^{\circ} R = (b_1, b_2, ...b_5) \tag{20}$$

5.2. Results and discussion

After solving the evaluation model, the total scores of factors and evaluation of HPCs on environment are calculated and listed in Table 5 as follows. It can be concluded that the PKU HPC, THU HPC and SJTU HPC have positive impacts on the environment. However, the CSU HPC and TC HPC have overall negative impacts on the environment instead as shown in Table 5.

Table 5. The total scores of factors and evaluation of HPCs on environment

	WRI	EWI	LUI	AQI	CUI	RCI	Rating	Results
PKU HPC	3.0	5.0	2.5	7.0	4.0	5.0	10.24	Positive
THU HPC	7.0	3.0	5.0	6.0	3.5	3.0	8.47	Positive
CSU HPC	5.5	6.0	3.0	4.0	6.0	7.0	-4.67	Negative
SJTU HPC	4.0	7.5	6.0	4.5	5	6.0	5.46	Positive
TC HPC	4.5	3.0	7.5	6.0	8.0	7.0	-6.24	Negative

5.3. Sensitivity analysis

In the part of sensitivity analysis, we define the maximum standard data as 100. Two parameter setting methods are constructed. When the data increased, the initial value was 0.01, the step length was 0.01, and the final value was -0.01; or when the data decreases, the initial value is -0.01, the step length is also 0.01, and the final value is -100.

Table 6. Estimated results by increasing the portion of renewable energy

Indicator variable	Value	Fluctuation threshold (%)	Range (%)
1	-7	3	10
2	-11	6	17
3	-3	4	7
4	-6	4	10

From the Table 6, we find that the sensitivity range under Water Resource Index (WRI) is 3%~4%, which is the most robust index, while the sensitivity range under Electronic Waste Index (EWI) is -11%~6%, which is the most sensitive index.

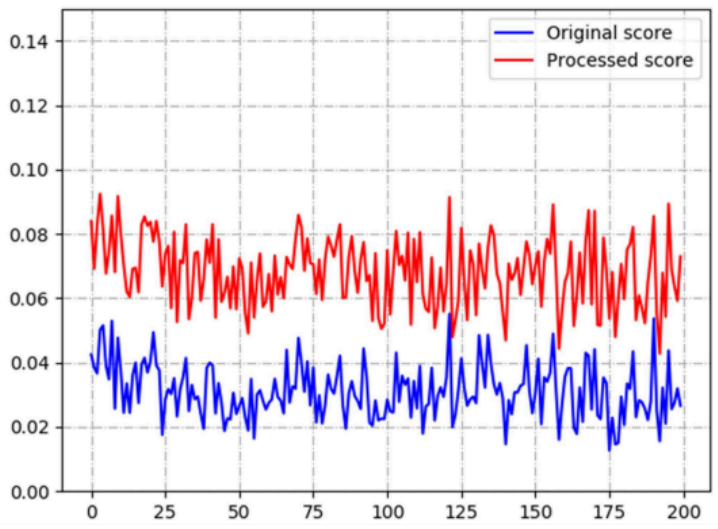


Figure 5. Sensitivity analysis

In order to observe the influence of the adjusted Water Resource Index (WRI) on the total score, we compared the schematic diagram of the original score and the adjusted score in the sensitivity analysis, where the red curve is the original score curve and the blue curve is the processed curve. Seen from the trend in the Figure 5, although the curve has changed in general, the trend has not changed significantly, which indicates that our evaluation system is stable and will not excessively affect the rating result due to change of indicators.

Next, to do the sensitivity analysis to the fuzzy integrated evaluation model, we use the random function to derive four standard matrices containing random integers between 1 to 10. The matrices are given in Table 7.

Table 7. Four random standard matrices for six indicators

	WRI	EWI	LUI	AQI	CUI	RCI
A1	9	6	6	1	5	4
A2	1	1	10	10	8	10
A3	10	3	10	10	1	8
	WRI	EWI	LUI	AQI	CUI	RCI
A1	10	9	8	7	0	1
A2	7	10	8	1	3	9
A3	0	7	4	7	0	7
	WRI	EWI	LUI	AQI	CUI	RCI
A1	3	4	8	4	8	7
A2	10	4	2	7	3	1
A3	0	8	5	7	7	1
	WRI	EWI	LUI	AQI	CUI	RCI
A1	6	5	2	9	1	9
A2	10	2	5	10	1	2
A3	3	8	7	6	2	8

The results are impressive. The matrices of the degree of membership and the corresponding heatmaps will be given below:

$$\begin{pmatrix} 5 & 7 & 6 \\ 6 & 6 & 7 \\ 6 & 4.5 & 4 \\ 5.5 & 5 & 5 \\ 4 & 7 & 7 \end{pmatrix} \quad \begin{pmatrix} 6 & 5 & 7 \\ 7 & 6.5 & 6 \\ 4 & 6 & 6 \\ 5 & 5.5 & 6 \\ 3 & 4 & 5.5 \end{pmatrix} \tag{21}$$

$$\begin{pmatrix} 5 & 7 & 7 \\ 5 & 7 & 6 \\ 6 & 5.5 & 5 \\ 6 & 4.5 & 6 \\ 6 & 6 & 5.5 \end{pmatrix} \quad \begin{pmatrix} 7 & 6 & 6 \\ 6 & 7 & 6 \\ 7 & 5 & 4.5 \\ 5 & 5 & 6 \\ 5 & 6 & 5 \end{pmatrix} \tag{22}$$

It can be seen that, in general, the stability of the model is marvelous. For the first random data, operating-related HPC has positive impacts on environment. For the second random data, the selected HPC has negative impacts on environment. As a result, in overview, in most of the time, the algorithm will behave well, generating the evaluation the impacts of HPC on environment.

6. Reducing the environmental impact of HPC

6.1. Actionable recommendations

We put forward some recommended measures to reduce the environmental hazards of High-Performance Computing (HPC) as follows. In terms of energy management, adopt efficient hardware, optimize data center layout, utilize renewable energy, and implement an intelligent energy management system. Choose hardware with high energy efficiency such as servers, processors, storage devices, etc. For example, using low-power Central Processing Units (cpus), Graphics Processing Units (GPUs), and accelerators with energy-saving features. This can provide powerful computing power while reducing energy consumption during device operation. Reasonably plan the placement of servers and other equipment inside the data center to ensure smooth air circulation for better heat dissipation and reduce the energy consumption of the cooling system. Technologies such as cold and hot channel isolation can be used to effectively separate cold air and hot air, improving cooling efficiency. Use renewable energy sources such as solar, wind, and hydro to power HPC systems as much as possible in data centers. For example, installing solar panels on the roofs of data center buildings or establishing partnerships with nearby renewable energy power plants to increase the proportion of renewable energy in power supply, reduce dependence on traditional fossil fuels, and lower carbon emissions. Install energy monitoring and management software to monitor the energy consumption of various parts of the HPC system in real time, and dynamically adjust the power supply and operation status of the equipment according to the actual load. For example, when the system load is low, automatically reducing the server's operating frequency or shutting down some unnecessary devices to save energy.

In terms of cooling technology, promote liquid cooling technology, waste heat recovery and utilization, and uses the natural cooling technology. Compared to traditional air-cooling technology, liquid cooling technology has higher cooling efficiency. Direct or indirect liquid cooling can be used to bring the coolant into direct or indirect contact with servers and other equipment, taking away heat and reducing the energy consumption and noise of the cooling system. The large amount of waste heat generated during the operation of the HPC system is recovered and used for other purposes, such as winter heating, hot water supply, etc. This can not only reduce energy waste, but also improve the comprehensive utilization rate of energy. In areas with suitable climate conditions, fully utilize natural cooling sources such as outdoor cold air, groundwater, etc. for natural cooling. For example, by introducing outdoor cold air into the data center or using groundwater to exchange heat with servers, the frequency of mechanical cooling system usage can be reduced.

In terms of electronic waste disposal, establish a comprehensive recycling system, design to improve the recycle possibility of equipment, and strengthening the resource utilization of electronic waste. Develop relevant policies and regulations for electronic waste recycling, establish a wide-ranging electronic waste recycling network, and ensure that HPC equipment can be properly recycled and disposed of after retirement. Encourage enterprises and users to proactively hand over their waste HPC equipment to legitimate recycling institutions. In the design phase of HPC equipment, the disassembly and recycling issues of the equipment are considered. Easy to disassemble structures and connection methods are adopted, and recyclable materials are used to facilitate disassembly and classification recycling after the equipment is retired. For recycled HPC electronic waste, advanced processing technologies such as physical separation and chemical extraction are used to recycle and reuse valuable materials such as metals and plastics, reducing resource waste and environmental pollution. As for the algorithm and software optimization, optimization algorithms and programs should be performed and adopting virtualization and container technology. Developers should strive to optimize the algorithms and code of HPC applications, improve program execution efficiency, reduce unnecessary calculations and data transmission, thereby reducing energy consumption. For example, adopting

more efficient numerical calculation methods, data compression techniques, etc. Through virtualization and container technology, multiple HPC tasks can be integrated and run on a single physical server, improving server utilization and reducing the number of physical servers, thereby reducing energy consumption and hardware resource utilization.

In terms of data management, data simplification and distributed storage optimization should also be performed. Filtering and cleaning data to remove unnecessary data and reduce the need for data storage and processing. At the same time, data compression technology is adopted to reduce the space occupation of data storage and the bandwidth requirements for transmission. Reasonably plan the layout and data allocation strategy of distributed storage systems, reduce data storage redundancy, improve data access efficiency, and reduce energy consumption of storage systems. As for the cultivating environmental awareness, training and education, promotion and advocacy should be performed and adopted. Provide environmental awareness and energy-saving technology training to HPC system management personnel, operation and maintenance personnel, and users to enhance their understanding of HPC environmental hazards and encourage them to actively take environmental protection measures in their daily work. Strengthen the promotion and advocacy of HPC environmental issues through various media and channels, increase the attention of the whole society to the impact of HPC on the environment, and promote the formation of a green and low-carbon HPC usage culture.

6.2. Incorporating into the improved model

6.2.1. Increasing the efficiency of energy management

When the efficiency of energy management is increased, the rate of using hardware with high energy efficiency R will increase gradually with the increase of the portion of renewable energy S. Herein, the Ordinary Differential Equation (ODE) to describe the change rate of R with S can be expressed as follows.

$$\frac{dR}{dS} = rR(1 - \frac{R}{K}) \tag{23}$$

Where r denotes the increasing rate of using hardware with high energy efficiency, and K represents the maximum of using hardware rate due to the limitation of the total hardware in this town. After solving this Ordinary Differential Equation (ODE), the analytical solution of this ODE could be determined as follows.

$$R(S) = \frac{KR_0e^{rS}}{K+R_0(e^{rS}-1)} \tag{24}$$

The expression above can be simplified into the following equation.

$$R(S) = \frac{1}{a+be^{-rS}} \tag{25}$$

Where a and b are two constant parameters in the analytical solution.

As illustrated in Figure 6, the Logistic function of rate of using hardware with high energy efficiency $R(S)$ indicates that the efficiency of energy management will increase gradually and then reach saturation at last, which could be explained by the limitation of the total number of hardware. The improvement of energy management efficiency is characterized by the variation in the adoption proportion of high-energy-efficiency hardware alongside changes in the share of renewable energy supply. This dynamic relationship is mathematically described by a logistic ordinary differential equation, whose analytical solution yields a sigmoidal functional form containing two lumped constant parameters. The plotted logistic curve presented in Figure 6 visualizes how energy management efficiency evolves as the quantity of deployed high-energy-efficiency hardware rises. Observed growth follows typical logistic behaviour, whereby efficiency rises progressively in the initial phase before gradually tapering off to a stable saturation plateau. Such

saturation behaviour arises from the finite total inventory of available hardware within the investigated town, which imposes an upper physical bound on the achievable adoption rate of high-efficiency hardware. Further increases in renewable energy proportion cannot drive continuous improvement in energy management performance once this limiting hardware capacity is approached.

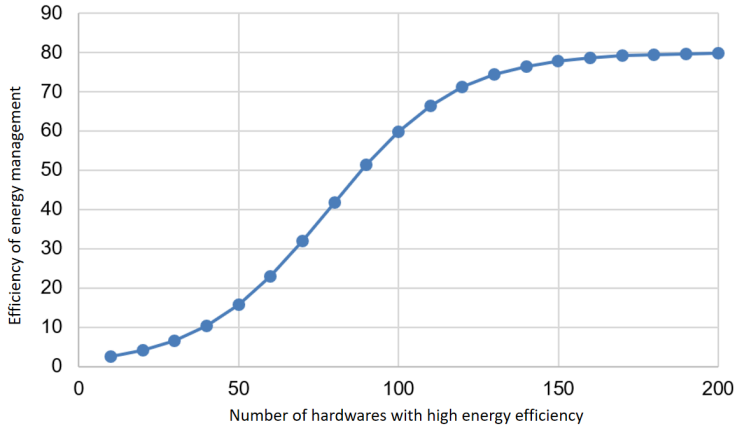


Figure 6. The curve of the logistic function to describe the rate of using hardware

6.2.2. Increasing the efficiency of cooling technology

Similarly, when the efficiency of cooling technology increases, the positive impacts of HPCs on environment will also increase. Nonetheless, the recovery and utilization of waste heat will also reach saturation in the end due to the limitation of the total HPCs and working time. Consequently, the recovery and utilization of waste heat could also be described by the logistic function and expressed as follows.

$$I(S) = \frac{MI_0 e^{\gamma S}}{M + I_0(e^{\gamma S} - 1)} \tag{26}$$

Where M denotes the maximum of recovery and utilization of waste heat and I_0 represents the initial average recovery and utilization of waste heat. Besides, S denotes the efficiency of cooling technology and γ represents the increasing rate of the efficiency of cooling technology.

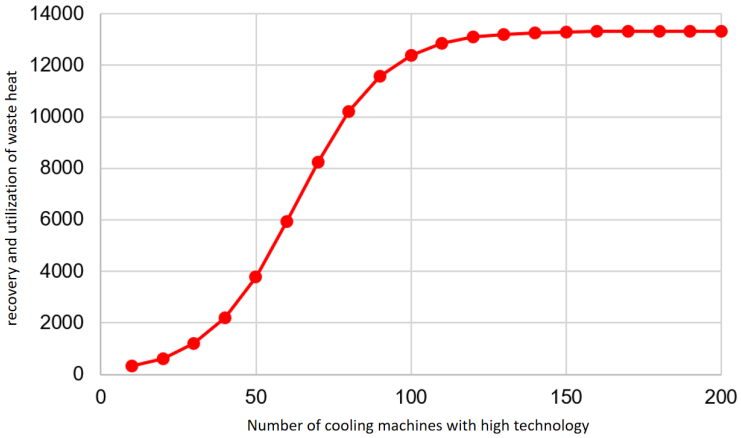


Figure 7. The curve of the logistic function to describe the recovery and utilization of waste heat

As shown in Figure 7, the Logistic function of recovery and utilization of waste heat $I(S)$ indicates that the recovery and utilization of waste heat $I(S)$ will increase gradually and then reach saturation, which could be

explained by the limitation of total HPCs and working time. Enhanced cooling technology efficiency delivers positive environmental outcomes for high-performance computing facilities, predominantly through improved waste-heat recovery and reuse. Constraints imposed by the total scale of high-performance computing infrastructure and feasible operational working hours prevent unbounded growth in waste-heat utilization capacity. A logistic function is therefore applied to capture this non-linear evolutionary trend of waste-heat recovery potential. The corresponding response curve in Figure 7 demonstrates that waste-heat recovery and utilization values increase steeply with growing numbers of high-technology cooling machines during early deployment stages. Growth momentum diminishes thereafter, and performance converges toward a predefined maximum recovery limit. The defined maximum parameter reflects the theoretical upper limit of recoverable waste heat under given infrastructure constraints, while the initial condition captures baseline waste-heat utilization prior to cooling-technology upgrades. These modelled dynamics indicate that marginal environmental benefits from additional high-technology cooling equipment gradually decline as the system nears its inherent operational ceiling.

6.2.3. Reducing electronic waste disposal

Nonetheless, the construction of HPCs also has several negative effects on the environment due to the releases of the electronic waste and gases. The concentration of the polluted air could be modeled based on the Partial Differential Equation (PDE) and be solved as follows:

$$c(x,y,z,H) = \frac{Q}{2\pi u\sigma_y\sigma_z}\, exp(-\frac{y^2}{2\sigma_y^2})\{exp[-\frac{(z-H)^2}{2\sigma_z^2}] + exp[-\frac{(z+H)^2}{2\sigma_z^2}]\} \tag{27}$$

Herein, $c(x,y,z,H)$ denotes the concentration of polluted gas at position (x,y,z) as shown in Figure 8 and H is the efficient height of the releasing of the polluted gas. Besides, u represents the speed of the polluted gas, Q is the initial concentration of the polluted gas, σ_y and σ_z are the diffusion coefficients of polluted gas on the y and z direction, respectively.

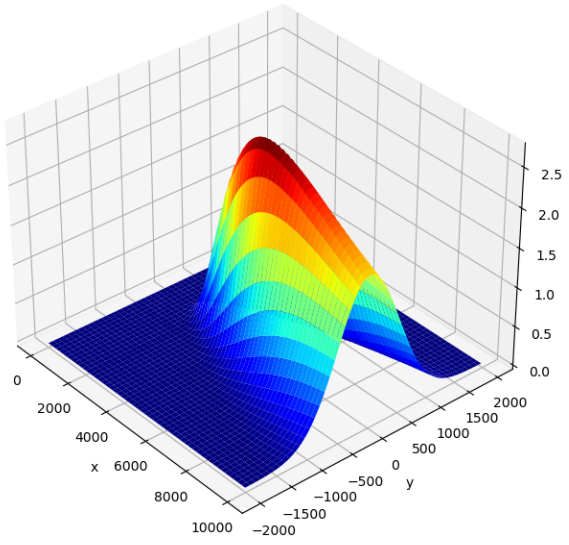


Figure 8. Distribution plot of concentration of polluted gas

High-performance computing construction generates adverse environmental externalizations through electronic-waste outputs and associated gaseous pollutant emissions. Spatial distributions of pollutant gas concentrations are quantified using a Gaussian-based partial differential equation solution that accounts for

three-dimensional spatial coordinates and the effective stack release height of pollutants. Input variables incorporate ambient transport wind speed, source pollutant emission strength, and lateral as well as vertical atmospheric diffusion coefficients that govern plume spreading behaviour. The three-dimensional concentration distribution illustrated in Figure 8 shows highest pollutant concentration values occurring in the spatial domain proximate to the emission source. Concentrations decay gradually along downwind and cross-wind directions under the combined effects of atmospheric diffusion. This modelled spatial pattern reveals that pollutant exposure levels vary substantially across different geographical locations surrounding high-performance computing deployments, with locations closer to emission sources subject to considerably higher contaminant loads.

6.2.4. Reducing noise pollution on residents

Here, the distribution plot of noise is similar to the polluted gas and can be expressed as follows:

$$N(x,y,z,H) = \frac{Q}{2\pi u\sigma_y\sigma_z}\, exp(-\frac{y^2}{2\sigma_y^2})\{exp[-\frac{(z-H)^2}{2\sigma_z^2}] + exp[-\frac{(z+H)^2}{2\sigma_z^2}]\} \tag{28}$$

Herein, $N(x,y,z,H)$ denotes the intensity of noise at position (x,y,z) as shown in Figure 9 and H is the efficient height of the releasing of the noise. Besides, u represents the speed of the noise, Q is the initial intensity of the noise, σ_y and σ_z are the spreading coefficients of noise on the y and z direction, respectively.

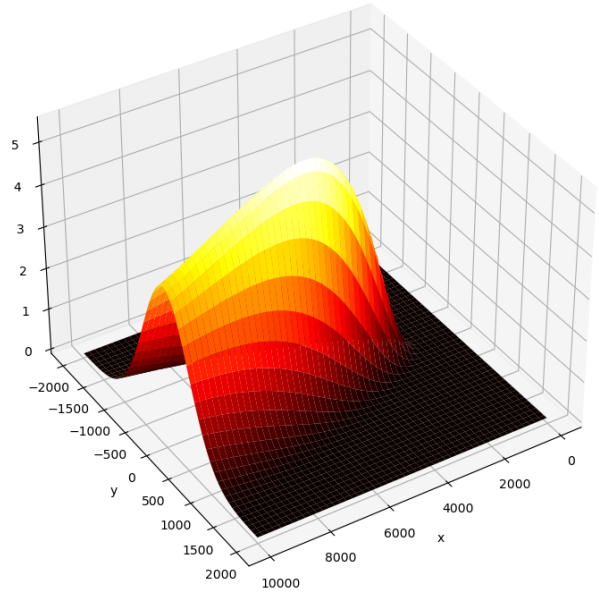


Figure 9. Distribution plot of intensity of noise

Spatial spreading characteristics of noise originating from high-performance computing facilities exhibit analogous physical behaviour to gaseous pollutant dispersion, justifying adoption of a structurally comparable mathematical formulation for noise-intensity modelling. The computed noise-intensity distribution visualized in Figure 9 illustrates peak noise magnitudes near the effective noise-release height, followed by progressive attenuation as distance increases in horizontal and vertical directions. Transport and spreading parameters embedded within the model represent noise propagation velocity, initial source noise intensity, and directional spreading coefficients for cross-wind and vertical dimensions. Heterogeneous noise exposure across residential zones can be directly inferred from this continuous spatial distribution. Residential areas situated closer to high-performance computing hardware installations are predicted to experience elevated noise intensity, whereas noise interference fades for communities located further away from emission sources.

7. Conclusion

In conclusion, we build the Analytic Hierarchy Process (AHP) model and Fuzzy Comprehensive Evaluation (FCE) model to evaluate the impact of HPCs on environment, and we collect some data on five HPCs to test our models. Finally, we use the real data of HPCs to test the sensitivity of our models. In addition, we also put forward some recommended measures to reduce the environmental hazards of High-Performance Computing (HPC), such as adopting efficient hardware, optimizing data center layout, utilizing renewable energy, implementing an intelligent energy management system, promoting liquid cooling technology, developing natural cooling technology, establishing a comprehensive recycling system, and strengthening the resource utilization of electronic waste. Collectively, the four modelled mechanisms capture both beneficial environmental gains from technical optimization and detrimental environmental burdens originating from high-performance computing hardware operation. Logistic-function representations for energy-management improvement and cooling-technology advancement explicitly incorporate real-world system limits, avoiding unrealistic unbounded performance improvement predictions. Dispersion-based modelling for gas pollution and noise pollution enables spatially explicit assessment of negative environmental impacts rather than relying solely on aggregated bulk-quantity estimations. Modelling outputs support rational evaluation of intervention measures, as technical upgrades produce diminishing-return benefits once system saturation thresholds are reached, while pollution mitigation requires consideration of spatial exposure patterns for surrounding residential populations. These simulation observations provide quantitative support for the comprehensive environmental assessment framework for high-performance computing facilities constructed in the overall study.

Author contribution

S.S. Wang designed the project and finalized the manuscript. Q.Y. An and B.E. Tang performed the modelling, calculations and analyses. All the authors participated in the discussion and preparation of the manuscript.

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Data availability

The authors confirm that the data supporting the findings of this study are available within the article.

Declarations

Competing interests Authors are required to disclose financial or non-financial interests that are directly or indirectly related to the work submitted for publication.

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