2025 5th International Conference on Artificial Intelligence and Industrial Technology Applications (AIITA)

Research on the Basic Methods of Collaborative Computing Power and Energy Evaluation Model in Intelligent Computing Center

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***Abstract*—As the digital economy advances, there is a surge in demand for intelligent computing power across diverse industries., the development of intelligent computing centers is currently facing an undeniable challenge - How to plan computing power and integrated energy supply to achieve collaborative development of computing power and energy. This paper proposes a collaborative computing power and energy evaluation model for intelligent computing centers. The evaluation process addresses the issue of varying measurement units among different types of indicators through the use of the model. Concurrently, It adopts a hybrid methodology, combining the bidirectional projection technique with the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach, to evaluate the comprehensive state of collaborative computing power and energy in a manner that is both scientifically rigorous and highly effective. Ultimately, the efficacy and practical application of the model are showcased through illustrative numerical scenarios.**

Keywords-intelligent computing center; energy consumption; computational effectiveness; carbon usage effectiveness; evaluation model

I. INTRODUCTION

The intelligent revolution driven by computing power is reshaping the law of economic operation, the way of social resource allocation, and the concept of national governance[1], which is the key element to enhance the competitiveness of urban economy and the degree of development[2]. In recent years, China has strengthened the construction of intelligent computing centers, promoted the innovative development of computing technology and industries, and provided fresh impetus to the high-quality progress of the economy and society.At the national level, the " Overall Layout Plan for the Construction of Digital China", ""Opinions on Promoting the Development of a National Unified Computing Power Grid by Enhancing the 'East Data, West Computing' Initiative", "Plan for Advancing the High-Quality Growth of Computing Power Infrastructure

"Special Action Plan for Green and Low Carbon Development of Intelligent Computing Centers" and other documents have put forward specific requirements to promote the high-standard advancement of intelligent computing hubs in China; At the local level, provinces and cities such as Beijing, Shanghai, Shandong, Jiangsu, Guizhou, and Shanxi have also issued relevant policies to clarify the high-quality development plan of intelligent computing centers in the coming years.

The industry has been constantly exploring how to measure and represent the collaborative computing power and energy of intelligent computing centers. The existing evaluation models often only focus on a single dimension, such as performance or energy consumption, and lack a comprehensive evaluation of the comprehensive benefits of multiple dimensions. Performance often only focuses on the computing power of the intelligent computing center, which refers to the ability to output results by processing data through intelligent computing servers. So far, the most widely used method for representing computing power is "floating-point operation count". Energy consumption may only focus on the power utilization efficiency (PUE) of the intelligent computing center. The significance of studying collaborative computing power and energy evaluation models lies in providing a systematic approach to comprehensively evaluate the collaborative performance computing power and energy in the intelligent computing center, optimize resource allocation and management strategies. By introducing multidimensional evaluation indicators such as energy consumption, carbon usage effectiveness, and computational efficiency, a computational model can be built to more accurately reflect the comprehensive benefits of the intelligent computing center in terms of the collaborative computing power and energy.

II. RELEVANT THEORIES

A. Group Decision-Making with Multiple Attributes

Alternative: Collaborative Decision-Making Involving Multiple Attributes [3-6] (MAGDM), as an important field of modern decision science, is suitable for situations with a limited number of alternative solutions and multiple evaluation criteria. Commonly employed techniques in multi-attribute decision-making include the Analytic Hierarchy Process (AHP) and the TOPSIS method (Technique for Order of Preference by

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Similarity to Ideal Solution)., as well as the Comprehensive Evaluation Approach, which are hot research directions in the academic community. At present, the evaluation of various indicators of the collaborative computing power and energy in intelligent computing centers can be summarized as a multi-attribute group decision-making problem. In order to comprehensively evaluate the level of collaborative computing power and energy, this paper proposes a collaborative computing power and energy evaluation model, which integrates and compares different dimensional indicators such as power usage effectiveness level, carbon usage effectiveness level, computational effectiveness level, universality level and openness level that are highly correlated with the collaborative computing power and energy of the intelligent computing center. The new bidirectional projection method [7] and TOPSIS method [8-12] are used to calculate the relative closeness of the samples, and then the collaborative computing power and energy of different samples are graded, solving the difficulty of directly comparing different dimensional variables and improving the comprehensiveness and effectiveness of the evaluation results. This paper provides new models and methods for the evaluation system of collaborative computing power and energy, better guiding and suggesting the industry to judge the development trend of intelligent computing centers, and providing ideas for future planning and deployment of intelligent computing centers.

B. Bidirectional Projection Model

The multi-attribute group decision-making problem constitutes a significant branch within decision theory and has found widespread application across numerous domains. The projection method [13] is highly apt for addressing decision-making challenges, as it effectively takes into account the distance among the evaluated entities, but also the angle between them. In certain instances, however, feasible solutions may be perpendicular to the line equidistant from both the positive and negative ideal solutions in real-world scenarios. traditional projection methods will face the problem of failure. The bidirectional projection method [14] can avoid problems that traditional projection methods cannot handle, and has the characteristics of scientific rationality, simplicity, and high discrimination. It has been widely promoted in practical decision-making. In this section, a bidirectional projection model is presented by integrating the bidirectional projection approach with the TOPSIS [8] method.

III. Calculation Capacity Evaluation Model

A. Selection of Evaluation Metrics

The objective of this research is to develop a thorough and pragmatic evaluation framework for assessing the performance and energy efficiency of collaborative computing systems, objectively assess the level of capacity quality development, and attempt to propose a high-quality collaborative computing power and energy evaluation model. The primary evaluation target of this system is the intelligent computing center, with the following principles guiding the selection of evaluation metrics. Firstly, it ensures that the evaluation metrics align with policy objectives and regional development needs; secondly, the evaluation model must comprehensively cover the key characteristics of the intelligent computing center's collaborative computing power and energy, ensuring that the evaluation results accurately reflect the intelligent computing center's collaborative computing power and energy; thirdly, the design of the evaluation model should be both theoretically sound and practically feasible; fourthly, the model must be capable of adapting to future technological advancements and policy changes. Based on these principles, a "five-in-one" evaluation system for the collaborative computing power and energy of the intelligent computing center is established from five dimensions: power usage effectiveness level, carbon usage effectiveness level, computational effectiveness level, universality level and openness level.

The goal of the evaluation is to gauge the energy efficiency of the intelligent computing center by analyzing its Power Usage Effectiveness (PUE) rating, which measures the energy consumption level. It can be evaluated using PUE, The goal of this study is to establish a comprehensive and practical assessment framework to evaluate the performance and energy efficiency of collaborative computing systems. This overall consumption includes not only the energy used by IT equipment but also by cooling systems, power distribution, and other associated infrastructure.

Carbon Usage Effectiveness Level: The carbon efficiency level aims to maximize computing power output while minimizing carbon emissions from the intelligent computing center. This is primarily assessed through two indicators: the low-carbon management capabilities of the intelligent computing center (procurement, design, construction, operation, and recycling) and the carbon efficiency of the intelligent computing center itself.

Computational Effectiveness Level: The computing effectiveness of the intelligent computing center represents the ratio of its computing power to the power consumption of all IT equipment. It reflects an efficiency that balances both the computing performance and power consumption of the intelligent computing center, specifically, the computing power generated per watt of power consumed by the IT equipment within the center. The unit of measurement for computing efficiency is GFLOPS/W (FP32).

Universality Level: The universality level evaluates whether the intelligent computing center can fulfill the diverse application needs across various scenarios and meet the affordable usage requirements of different industries. This assessment is primarily based on two comprehensive indicators: universality and inclusiveness.

Openness Level: The openness level examines the degree of technological compatibility, supply chain completeness, and industrial ecological openness within the intelligent computing center. This is evaluated through three key indicators: technological compatibility, supply chain completeness, and the level of industrial ecological openness.

The evaluation measurement indicators are based on actual data from the intelligent computing center. The data on power usage effectiveness level, carbon usage effectiveness level, and computational effectiveness level mainly based on actual measurements by the intelligent computing center, and the specific measurement methods and errors can be conducted according to relevant standards. The data on universality level and openness level mainly based on subjective scores within the range of 0 - 5 given by industry experts according to the application scenarios, carried - out business operations, service targets, industrial partners, and other situations of the intelligent computing center.

B. Determine the Weights

To improve the scientific validity of the decision-ranking results in this paper, we address the inherent limitations present in both subjective and objective weighting methods, a hybrid weighting method is employed. This approach aims to reflect the expertise of relevant experts and practitioners, effectively avoiding the problem of mismatched importance when relying solely on purely objective methods to determine weights. It also aims to reflect the objective information of the indicator data, to some extent reducing the interference of subjective factors. The Analytic Hierarchy Process (AHP) is utilized to determine subjective weights, while the improved CRITIC method is applied to derive objective weights.

During the 1970s, Thomas L. Saaty presented a novel approach known as the Analytic Hierarchy Process (AHP), an American expert in operations research. This approach, which combines both qualitative and quantitative factors for multi-criteria analysis, is widely utilized in management decision-making, and it typically consists of three main stages: constructing the judgment matrix and assigning values; conducting pairwise comparisons and consistency checks at each level of the hierarchy; and performing the overall ranking and consistency checks at the entire hierarchy.

In multi-attribute decision-making problems, Diakoulaki's CRITIC method serves as an objective technique for allocating weights. It effectively avoids the uncertainty and arbitrariness caused by subjective weights. The degree of variation in data can be quantified using either standard deviation or variance, with the conventional CRITIC method opting for standard deviation to represent this variability. However, in real-world applications, mean deviation proves to be a more effective measure as it provides a comprehensive and unbiased reflection of data variability. Consequently, this research adopts an enhanced CRITIC method that utilizes mean deviation to ascertain weights. Compared to the traditional CRITIC method, the improved CRITIC method considers both the influence between indicators and the variability of data.

C. Model Construction

In this section, the information measured in the intelligent computing center is combined with the bidirectional projection model. A decision-making model is presented to process the information among different indicators f the intelligent computing center's collaborative computing power and energy using the bidirectional projection method. A collaborative computing power and energy evaluation model is constructed. Through case analysis, it is demonstrated that this decision - making model has a good effect. The specific steps of the model are as follows:

Step 1: Construct a decision matrix with hierarchical variables. Divide the indicators into levels based on the data, Identify the highest and lowest values from the available data, and then evenly distribute the desired number of levels between these extreme values. Generally speaking, the more ideal the value, the higher the level value marked on one end.

Step 2: Perform correlation transformation on the level variables through the generalized ordinal number operation mentioned above. Grade the data and convert it into a prime number (a real number between 0-1). The level table divided according to step 1 corresponds to the existing data. Match the data under each indicator to determine the corresponding level number. Under each indicator, compare the number of levels of different intelligent computing centers pairwise to obtain the number of levels that one intelligent computing center is better or worse than another intelligent computing center under a certain indicator. Convert the number of each level to between 0-1 using the formula for calculating the priority number, to facilitate subsequent processing.

Step 3: In multi-attribute decision-making problems, Diakoulaki's CRITIC method serves as an objective technique for allocating weights, compute the corresponding vectors by determining the maximum and minimum priority values among the indicators. This process entails identifying the optimal and least favorable solutions.

Step 4: calculate the projection values corresponding to each intelligent computing center separately.

Step 5: Compute the proximity of each intelligent computing center's calculation scheme to the ideal scheme.

Step 6: Rank the intelligent computing centers based on their relative closeness values, and assign a star rating accordingly. Select the solution with the greatest closeness, and ultimately summarize the findings.

IV. Evaluation Case Analysis

The data of five indicators (power usage effectiveness level, carbon usage effectiveness level, computational effectiveness level, universality level and openness level) corresponding to six intelligent computing centers are given, as shown in Table I.

TABLE I. SAMPLE DATA

No.	Power Usage Effectiveness Level	Carbon Usage Effectiveness Level	Computational Effectiveness Level	Universality Level	Openness Level
AIDC. 1	1.15	50.61	72	3.5	3.7
AIDC. 2	1.05	88.35	40.3	4.6	4.4
AIDC. 3	1.21	547.23	23.9	3.3	2.8
AIDC. 4	1.24	100.32	100	3.1	4.2
AIDC. 5	1.07	45.03	80.44	1.5	2.7
AIDC. 6	1.35	640.65	313.24	1.1	2.1

According to the experts' experience and data distribution, the assessment steps are as follows:

Step 1: Assign ratings to the five chosen indicators based on the data presented in Table II.

TABLE II. FIVE FORCE INDEX GRADING OF INTELLIGENT COMPUTING CENTER

No.	Tier I	Tier II	Tier III	Tier IV	Tier V
Power Usage Effectiveness Level	$>$ 1.4	1.3-1.4	1.2-1.3	1.1.-1.2	1.0-1.1
Carbon Usage Effectiveness Level	500-1000	230-500	130-230	90-130	0-90
Computational Effectiveness Level	0-10	10-20	20-30	30-50	50-100
Universality Level	0-1	1-2	2-3	3-4	4-5
Openness Level	0-1	1-2	2-3	3-4	4-5

Step 2: grade the data in Table I according to the grading table of intelligent computing center's computing power indicators in Table II. Under each indicator, compare the number of grades of each intelligent computing center in pairs to obtain the relative number of grades and convert it into an optimal number, as shown in Table III and Table IV below;

TABLE III. DRADING OF COMPUTING POWER INDEX OF INTELLIGENT COMPUTING CENTER

No.	Power Usage Effectiveness Level	Carbon Usage Effectiveness Level	Computational Effectiveness Level	Universality Level	Openness Level
AIDC.1	4	5	5	4	4
AIDC.2	5	5	4	5	5
AIDC.3	3	1	3	4	3
AIDC.4	3	4	5	4	5
AIDC.5	5	5	5	2	3
AIDC.6	2	1	2	2	3

TABLE IV. CONVERSION TABLE OF INTELLIGENT COMPUTING CENTER LEVEL COMPARISON LEVEL BY OPTIMAL ORDINAL NUMBER

No.	Power Usage Effectiveness Level	Carbon Usage Effectiveness Level	Computational Effectiveness Level	Universality Level	Openness Level
AIDC.1	[0,-0.57,0.57,0.57,-0.57,0.67]	[0,0,1,0.57,0,1]	[0,0.57,0.67,0,0,0.8]	[0,-0.57,0,0,0.67,0.67]	[0,-0.57,0.57,-0.57,0.57,0.57]
AIDC.2	[0.57,0,0.67,0.67,0,0.8]	[0,0,1,0.57,0,1]	[-0.57,0,0.57,-0.57-0.57,0.67]	[0.57,0,0.57,0.57,0.8,0.8]	[0.57,0,0.67,0,0.67,0.67]
AIDC.3	[-0.57,-0.67,0,0,-0.67,0.57]	[-1,-1,0,-0.8,-1,0]	[-0.67,-0.57,0,-0.67,-0.67,0.57]	[0,-0.57,0,0,0.67,0.67]	[-0.57,-0.67,0,-0.67,0,0]
AIDC.4	[-0.57,-0.67,0,0,-0.67,0.57]	[-0.57,-0.57,0.8,0,-0.57,0.8]	[0,0.57,0.67,0,0,0.8]	[0,-0.57,0,0,0.67,0.67]	[0.57,0,0.67,0,0.67,0.67]
AIDC.5	[0.57,0,0.67,0.67,0,0.8]	[0,0,1,0.57,0,1]	[0,0.57,0.67,0,0,0.8]	[-0.67,-0.8,-0.67,-0.67,0,0]	[-0.57,-0.67,0,-0.67,0,0]
AIDC.6	[-0.67,-0.8,-0.57,-0.57,-0.8,0]	[-1,-1,0,-0.8,-1,0]	[-0.8,-0.67,-0.57,-0.8,-0.8,0]	[-0.67,-0.8,-0.67,-0.67,0,0]	[-0.57,-0.67,0,-0.67,0,0]

Step 3: Identify the optimal and non-optimal solutions, then compute and ascertain the associated vectors accordingly.

Using Table IV as a reference, determine the optimal and worst-case ideal solutions. Subsequently, calculate the distance of each intelligent computing center's index measurements from these ideal solutions. It is clear that AIDC.6 performs the worst overall, while AIDC.1 and AIDC.2 show comparatively better overall performance.

Step 4: calculate the corresponding projection value;

The corresponding modules are obtained as follows:

$$|A^-A^+| \approx 3.3392 \tag{1}$$

$$|A^-A_1| \approx 2.6915 \tag{2}$$

$$|A_1A^+| \approx 1.0077 \tag{3}$$

$$|A^-A_2| \approx 3.2149 \tag{4}$$

$$|A_2A^+| \approx 0.5793 \tag{5}$$

$$|A^-A_3| \approx 1.0807 \tag{6}$$

$$|A_3A^+| \approx 2.7735 \tag{7}$$

$$|A^-A_4| \approx 2.3621 \tag{8}$$

$$|A_4A^+| \approx 1.4385 \tag{9}$$

$$|A^-A_5| \approx 2.6882 \tag{10}$$

$$|A_5A^+| \approx 1.9808 \tag{11}$$

$$|A^-A_6| \approx 0 \tag{12}$$

$$|A_6A^+| \approx 3.3392 \tag{13}$$

AIDC.1, AIDC.2, AIDC.4, AIDC.5 are relatively good, AIDC.3, AIDC.6 are relatively poor, which coincides with the final conclusion. The following process is used to obtain the projection value:

$$\Pr j_{A^-A^+}(A^-A_1) \approx 2.5085 \tag{14}$$

$$\Pr j_{A_1A^+}(A^-A^+) \approx 2.2966 \tag{15}$$

$$\Pr j_{A^-A^+}(A^-A_2) \approx 3.1669 \tag{16}$$

$$\Pr j_{A_2A^+}(A^-A^+) \approx 1.3528 \tag{17}$$

$$\Pr j_{A^-A^+}(A^-A_3) \approx 0.7713 \tag{18}$$

$$\Pr j_{A_3A^+}(A^-A^+) \approx 3.1156 \tag{19}$$

$$\Pr j_{A^-A^+}(A^-A_4) \approx 2.1685 \tag{20}$$

$$\Pr j_{A_4A^+}(A^-A^+) \approx 2.3606 \quad (21)$$

$$\Pr j_{A^-A^+}(A^-A_5) \approx 2.1642 \quad (22)$$

$$\Pr j_{A_5A^+}(A^-A^+) \approx 1.9808 \quad (23)$$

$$\Pr j_{A^-A^+}(A^-A_6) = 0 \quad (24)$$

$$\Pr j_{A_6A^+}(A^-A^+) \approx 3.3391 \quad (25)$$

Step 5: Compute the relative proximity of each intelligent computing center using the provided formula.

$$C(A_6) = 0 \quad (26)$$

$$C(A_1) \approx 0.5220 \quad (27)$$

$$C(A_2) \approx 0.7007 \quad (28)$$

$$C(A_3) \approx 0.1984 \quad (29)$$

$$C(A_4) \approx 0.4788 \quad (30)$$

$$C(A_5) \approx 0.5221 \quad (31)$$

Step 6: Rank the intelligent computing centers based on their relative closeness values, assign a star rating to each center according to Table V, and ultimately draw a conclusion.

TABLE V. CORRESPONDENCE TABLE OF RELATIVE CLOSENESS AND STAR RATING

Relative Closeness	0-0.15	0.15-0.30	0.30-0.50	0.50-0.70	0.70-1.0
Grade	★	★★	★★★	★★★★	★★★★★

Corresponding to:

AIDC.1 ★★★★ AIDC.2 ★★★★★ AIDC.3 ★★

AIDC.4 ★★★ AIDC.5 ★★★★ AIDC.6 ★

V. CONCLUSIONS

The intelligent computing center acts as a fundamental support for the advancement of higher-level application scenarios, including artificial intelligence, the Internet of Things, and AR/VR. Simultaneously, the rapid proliferation of these application scenarios imposes higher demands on the collaborative computing power of the intelligent computing center. Existing enterprises have innovated and optimized power supply and distribution technology, server hardware architecture, software platform, network connection, and security mechanism [15-17] to better meet the development needs of intelligent computing services.

Based on research on the collaborative computing power and energy of intelligent computing centers, this paper proposes a computational energy evaluation model. Initially, the intelligent computing center is graded based on power usage effectiveness level, carbon usage effectiveness level, computational effectiveness level, universality level and openness level. Subsequently, the bidirectional projection method and TOPSIS method are applied to evaluate each intelligent computing center. Ultimately, by comparing relative closeness values, different intelligent computing centers are rated with star ratings. This model enhances the differentiation of results, providing a more accurate reflection of the relative strengths and weaknesses among various intelligent computing centers. However, the approach proposed in this paper does not account for data measurement errors or consider whether a fixed ratio between different indicators optimizes overall efficiency. These aspects will be explored in future research.

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