Five Forces Model of Computational Power: A Comprehensive Measure Method

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Abstract

In this paper, a model is proposed to comprehensively evaluate the computational power. The five forces model of computational power solves the problem that the measurement units of different indexes are not unified in the process of computational power evaluation. It combines the bidirectional projection method with TOPSIS method. This model is more scientific and effective in evaluating the comprehensive situation of computational power. Lastly, an example shows the validity and practicability of the model.

Keywords: Computational power, Computational efficiency, Computational infrastructure, Data center, TOPSIS

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1. Introduction

In the era of digital economy, everything is connected to produce all kinds of big data. Data has become the fifth factor of production besides labor, capital, land and technology. Recently, data center became an important part of information infrastructure. It can be said that the takeoff of digital economy cannot be achieved without the support of computational power, and the development of computational power cannot be separated from data centers.

The industry has been constantly explored how computational power is measured and represented. In a narrow sense, computational power is a capability of a server to achieve result output by processing data. Up to now, the most widely used representation of computational power is floating point operations per second (FLOPS), the number of floating point operations performed per second, which was first published by Frank H. McMahon [1]. Many domestic and foreign literature and server product parameters use floating point operation times to describe the computational power. For example, Y. Sun et al. [2] used FLOPS as a metric to evaluate single and double precision computational capabilities of CPU and GPU [3]. Therefore, a scientific method is urgently needed to fully express the connotation of computational power.

Multi-attribute group decision making [4-7] is an intersection of multi-attribute decision making and group decision making. It is a significant research field and has been generally used in urban planning, investment risk and other areas. At present, the problem of evaluating various metrics for computational power synthesis among different data centers could be summarized as a multi-attribute group decision problem. In order to evaluate the computational power comprehensively, this paper puts forward the "five forces model". The model integrates and compares the general computational power, intelligent computational power, computational efficiency, storage capacity and network capacity, which are highly related to the computational power of the data center. It uses the new two-way projection method [8] and TOPSIS method [9-11] to calculate the relative closeness of samples. Then the computational power of different samples is graded, which solves the difficulty of direct comparison of different dimensional variables, and improves the comprehensiveness and effectiveness of evaluation results. This paper provides a new model and method for computational power evaluation system, better guide and advise the industry to judge the development trend of the industry, and provide ideas for computational power planning and deployment.

2. Related Theories

2.1 Related definitions

In multi-attribute decision making, the scheme set is $A = \{a_1, a_2, \cdots, a_s\}$, and the attribute set is $C = \{c_1, c_2, \cdots, c_m\}$, $S = \{1,2,\cdots,s\}$, $M = \{1,2,\cdots,m\}$ represents the sequence number of the scheme and the attribute, respectively. $c_l(A), l \in M$is used to represent the value of scheme A under the attribute$c_l$and allow for non-comparability.

Definition 1 [12] If relation $\{\succ, \prec, \approx, ?\}$ satisfies the following conditions: the ordinal preference information between schemes under each attribute can be given by the decision maker; for attribute $c_l, l \in M$, any two schemes a_i, $a_j (i \neq j)$ and satisfy one of the following preference relations: a_i is superior to a_j $(a_i \succ a_j)$; a_i is as good as a_j $(a_i \approx a_j)$; a_i is worse than a_j $(a_i \prec a_j)$; The relationship between a_i and a_j is unclear $(a_i ? a_j)$.

Only one of $\{\succ, \prec, \approx, ?\}$ relations is true between the two schemes a_i and a_j (satisfy $i \neq j$), then $\{\succ, \prec, \approx, ?\}$ is said to constitute a partial order preference structure. The attribute values of each scheme under different attributes are divided into N+1 levels, so that the degree of one scheme is better than another scheme is divided into N levels. Let's call it $a_i \overset{k}{\succ} a_j$, $(i, j \in S; 0 \leq k \leq n)$, which means a_i is superior to a_j by k grades; $a_i \overset{-k}{\succ} a_j, (i, j \in S; 0 \leq k \leq n)$and $a_i \overset{k}{\prec} a_j$, $(i, j \in S; 0 \leq k \leq n)$ all indicate that a_i is inferior to a_j by k grades.

Definition 2 In multi-attribute decision making, for convenience, $a_i \overset{t}{\succ} a_k$ is denoted as $r_t t \in \{-(n-1), \cdots, -1,0,1, \cdots, n-1\}$, and (1) is called hierarchical comparison set.

$$R = \{r_t | t = -(n-1), -(n-2), \cdots, -1,0,1, \cdots, n-2, n-1\} \tag{1}$$

The hierarchical comparison set satisfies the characteristics: (1) The set R is ordered: if $\alpha > \beta$, then $r_\alpha > r_\beta$; (2) There exists a negation operator: $neg(r_\alpha) = r_{-\alpha}$; (3) If $r_\alpha > r_\beta$, $max\{r_\alpha, r_\beta\} = r_\alpha$, $min\{r_\alpha, r_\beta\} = r_\beta$.

For any degree of comparison $r_\alpha, r_\beta \in R$, there are three basic operators: : $r_\alpha \oplus r_\beta = r_{\alpha+\beta}, r_\alpha \ominus r_\beta = r_{\alpha-\beta}$ and $\lambda r_\alpha = r_{\lambda\alpha}$.

The concept of generalized superior Ordinal Numbers is introduced below.

Definition 3 [13] Makes

$$a_{ijl} = \begin{cases} 1, c_l(A_i) \overset{n}{\succ} c_l(A_j), i \neq j \\ \frac{n}{2n-k}, c_l(A_i) \overset{k}{\succ} c_l(A_j), i \neq j \\ 0.5, c_l(A_i) \approx c_l(A_j), i \neq j \\ 0.375, c_l(A_i) ? c_l(A_j), i \neq j \\ 0, i = j \\ -\frac{n}{2n-k}, c_l(A_i) \overset{-k}{\succ} c_l(A_j), i \neq j \\ -1, c_l(A_i) \overset{-n}{\succ} c_l(A_j), i \neq j \end{cases} \tag{2}$$

Among them $i, j \in S, l \in M$. a_{ijl} is called the generalized superior ordinal number of scheme A_i relative to scheme A_j under the attribute c_l. To make the decision result more real and reliable, five forces model combined with the concept of vector, through the transformation of vector and correlation calculation, the application of bi-directional projection method and TOPSIS method, through the size of the relative closeness to get the relevant conclusion.

Definition 4 Let $X_p = [\underline{r}_{pj}, \bar{r}_{pj}]$ and $X_q = [\underline{r}_{qj}, \bar{r}_{qj}]$ be two uncertain grade variables on set X. If we transform X_p and X_q into $X_p = [\xi(\underline{r}_{pj}), \xi(\bar{r}_{pj})]$ and $X_q = [\xi(\underline{r}_{qj}), \xi(\bar{r}_{qj})]$ by generalized superior ordinal number, where $\xi(\underline{r}_{pj})$ is the value of $\underline{r}_{pj}$ transformed by generalized superior ordinal number, and other similar symbols have the same meaning, the vector formed by X_p and X_q is defined as follows:

$$X_pX_q = [min\,\xi(\underline{r}_{pj}), max\,\xi(\bar{r}_{pj})] \tag{3}$$

Among them:

$$min\,\xi(\underline{r}_{pj}) = min\left(\left|\xi(\underline{r}_{qj}) - \xi(\underline{r}_{pj})\right|, \left|\xi(\bar{r}_{qj}) - \xi(\bar{r}_{pj})\right|\right),$$
$$max\,\xi(\bar{r}_{pj}) = max\left(\left|\xi(\underline{r}_{qj}) - \xi(\underline{r}_{pj})\right|, \left|\xi(\bar{r}_{qj}) - \xi(\bar{r}_{pj})\right|\right).$$

Let $A = \{a_1, a_2, \cdots, a_m\}$ be the scheme set, $C = \{c_1, c_2, \cdots, c_n\}$ be the attribute set, and attribute $c_l (1 \le l \le n)$ be divided into 5 grades. There is a grade comparison set $R = \{r_i | i = -4, \cdots, 0, \cdots, 4, ?\}$, where?represents the case where the merits and demerits of the two schemes are unknown, and $t = 4$. We know that the two rank variables are $X_p = [r_2, r_3]$ and $X_q = [r_3, r_4]$.

$X_p = [r_2, r_3]$ and $X_q = [r_3, r_4]$ can be transformed into $X_p = \left[\frac{2}{3}, \frac{4}{5}\right]$ and $X_q = \left[\frac{4}{5}, 1\right]$ by means of generalized superior ordinal number. Then, through definition 4, the vector formed by X_p and X_q is calculated as $X_pX_q = \left[\frac{2}{15}, \frac{3}{15}\right]$.

2.2 Bidirectional Projection Model

Projection method [14] is a appropriate method to dispose of decision problems. However, in some cases, the traditional projection method will be ineffective. Bidirectional projection [8] can handle problems that traditional projection method cannot handle. It has the characteristics of scientific rationality, simplicity and high distinction. This section combines the bidirectional projection method and TOPSIS method [15] to give a bidirectional projection model.

Assume that $X_i = [\xi(\underline{r}_{ij}^t), \xi(\bar{r}_{ij}^t)]$ is the information of the grade transformation of alternative X_i under the j-th attribute c_j.

Firstly, under attribute j, positive and negative ideal schemes are expressed as $X^+ = [\max_{1\le i\le n}\xi(\underline{r}_{ij}), \max_{1\le i\le n}\xi(\bar{r}_{ij})]$, $X^- = [\min_{1\le i\le n}\xi(\underline{r}_{ij}), \min_{1\le i\le n}\xi(\bar{r}_{ij})]$, where n is the number of overall alternatives. According to Definition 4, the vector formed by positive and negative ideal schemes could be calculated and presented as $X^-X^+ = [\xi(\underline{r}_{ij}^t), \xi(\bar{r}_{ij}^t)]$, where:

$$\xi(\underline{r}_{ij}^t) = min\left(\left(\max_{1\le i\le n}\xi(\underline{r}_{ij}) - \min_{1\le i\le n}\xi(\underline{r}_{ij})\right), \left(\max_{1\le i\le n}\xi(\bar{r}_{ij}) - \min_{1\le i\le n}\xi(\bar{r}_{ij})\right)\right)$$
$$\xi(\bar{r}_{ij}^t) = max\left(\left(\max_{1\le i\le n}\xi(\underline{r}_{ij}) - \min_{1\le i\le n}\xi(\underline{r}_{ij})\right), \left(\max_{1\le i\le n}\xi(\bar{r}_{ij}) - \min_{1\le i\le n}\xi(\bar{r}_{ij})\right)\right)$$

Also according to definition 4, under attribute j, the vector formed by X_i and positive and negative ideal schemes X^+, X^- is expressed as $X^-X_i = [\xi(\underline{r}_{ij}^-), \xi(\bar{r}_{ij}^-)]$, $X_iX^+ = [\xi(\underline{r}_{ij}^+), \xi(\bar{r}_{ij}^+)]$, where,

$$\xi\left(\underline{r}_{ij}^{-}\right) = min\left(\left(\xi\left(\underline{r}_{ij}\right) - \min_{1\le i\le n}\xi\left(\underline{r}_{ij}\right)\right), \left(\xi(\bar{r}_{ij}) - \min_{1\le i\le n}\xi(\bar{r}_{ij})\right)\right)$$
$$\xi(\bar{r}_{ij}^{-}) = max\left(\left(\xi\left(\underline{r}_{ij}\right) - \min_{1\le i\le n}\xi\left(\underline{r}_{ij}\right)\right), \left(\xi(\bar{r}_{ij}) - \min_{1\le i\le n}\xi(\bar{r}_{ij})\right)\right)$$
$$\xi\left(\underline{r}_{ij}^{+}\right) = min\left(\left(\max_{1\le i\le n}\xi\left(\underline{r}_{ij}\right) - \xi\left(\underline{r}_{ij}\right)\right), \left(\max_{1\le i\le n}\xi(\bar{r}_{ij}) - \xi(\bar{r}_{ij})\right)\right)$$
$$\xi(\bar{r}_{ij}^{+}) = max\left(\left(\max_{1\le i\le n}\xi\left(\underline{r}_{ij}\right) - \xi\left(\underline{r}_{ij}\right)\right), \left(\max_{1\le i\le n}\xi(\bar{r}_{ij}) - \xi(\bar{r}_{ij})\right)\right)$$

The modulus of the corresponding vector can be calculated by the following formula:

$$|X^{-}X^{+}| = \sqrt{\sum_{j=1}^{m}\left(\left(\xi\left(\underline{r}_{ij}^{t}\right)\right)^{2} + \left(\xi(\bar{r}_{ij}^{t})\right)^{2}\right)}$$
$$|X^{-}X_{i}| = \sqrt{\sum_{j=1}^{m}\left(\left(\xi\left(\underline{r}_{ij}^{-}\right)\right)^{2} + \left(\xi(\bar{r}_{ij}^{-})\right)^{2}\right)}$$
$$|X_{i}X^{+}| = \sqrt{\sum_{j=1}^{m}\left(\left(\xi\left(\underline{r}_{ij}^{+}\right)\right)^{2} + \left(\xi(\bar{r}_{ij}^{+})\right)^{2}\right)}$$

Then, the cosine values $cos(X^{-}X_{i}, X^{-}X^{+})$ and $cos(X^{-}X_{i}, X^{-}X^{+})$ can be calculated as:

$$cos(X^{-}X_{i}, X^{-}X^{+}) = \frac{\sum_{j=1}^{m}\left(\xi\left(\underline{r}_{ij}^{t}\right)\cdot\xi\left(\underline{r}_{ij}^{-}\right) + \xi\left(\bar{r}_{ij}^{t}\right)\cdot\xi\left(\bar{r}_{ij}^{-}\right)\right)}{|X^{-}X_{i}|\cdot|X^{-}X^{+}|} \tag{4}$$
$$cos(X^{-}X_{i}, X^{-}X^{+}) = \frac{\sum_{j=1}^{m}\left(\xi\left(\underline{r}_{ij}^{t}\right)\cdot\xi\left(\underline{r}_{ij}^{+}\right) + \xi\left(\bar{r}_{ij}^{t}\right)\cdot\xi\left(\bar{r}_{ij}^{+}\right)\right)}{|X_{i}X^{+}|\cdot|X^{-}X^{+}|} \tag{5}$$

Then, the projection values of vectors $X^{-}X_{i}$ to $X^{-}X^{+}$ and $X^{-}X^{+}$ to $X_{i}X^{+}$ are:

$$\begin{aligned} prj_{X^{-}X^{+}}(X^{-}X_{i}) &= |X^{-}X_{i}|\cdot cos(X^{-}X_{i}, X^{-}X^{+}) \\ &= \frac{\sum_{j=1}^{m}\left(\xi\left(\underline{r}_{ij}^{t}\right)\cdot\xi\left(\underline{r}_{ij}^{-}\right) + \xi\left(\bar{r}_{ij}^{t}\right)\cdot\xi\left(\bar{r}_{ij}^{-}\right)\right)}{|X^{-}X^{+}|} \end{aligned} \tag{6}$$
$$\begin{aligned} prj_{X_{i}X^{+}}(X^{-}X^{+}) &= |X^{-}X^{+}|\cdot cos(X_{i}X^{+}, X^{-}X^{+}) \\ &= \frac{\sum_{j=1}^{m}\left(\xi\left(\underline{r}_{ij}^{t}\right)\cdot\xi\left(\underline{r}_{ij}^{+}\right) + \xi\left(\bar{r}_{ij}^{t}\right)\cdot\xi\left(\bar{r}_{ij}^{+}\right)\right)}{|X_{i}X^{+}|} \end{aligned} \tag{7}$$

Note 1: In the **Fig. 1**, the higher value of $prj_{X^{-}X^{+}}(X^{-}X_{i})$ is, the closer X_{i} is to X^{+} ; On the contrary, the larger $prj_{X_{i}X^{+}}(X^{-}X^{+})$ is, the closer X_{i} is to X^{-}. Accordingly, the pros and cons of each alternative scheme can be judged according to the calculation of their projection values.

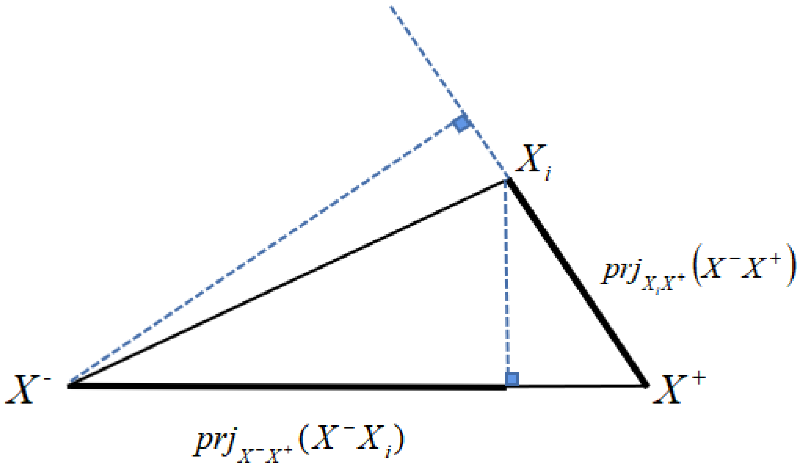


Fig. 1. the projection values of vectors X^-X_i to X^-X^+ and X^-X^+ to X_iX^+

Through calculation, the projection formula describes the similarity and considers the distance (value) and direction between the alternative plan and the positive and negative ideal plan. In order to make the result more accurate and reasonable, alternative plan X_iX_i needs to be combined with the projection of positive and negative rational plan X^+X^+ and X^-, which is represented by relative closeness degree $C(X_i)$ and calculated by the following formula:

$$C(X_i) = \frac{prj_{X^-X^+}(X^-X_i)}{prj_{X^-X^+}(X^-X_i)+prj_{X_iX^+}(X^-X^+)} \tag{8}$$

where $prj_{X^-X^+}(X^-X_i)$ and $prj_{X_iX^+}(X^-X^+)$ represent the projection values of vectors X^-X_i to X^-X^+ and X^-X^+ to X_iX^+ severally .

On these basis , the specific steps of hierarchical bidirectional projection model are as shown below :

Step 2.2.1: Construct decision moment D with rank variables and normalize it;

Step 2.2.2: Correlation transformation of grade variables is carried out through the above generalized superior ordinal number operation;

Step 2.2.3: Determine positive ideal scheme $X^+ = \{X_1^+, X_2^+, \cdots, X_m^+\}$ and negative ideal scheme $X^- = \{X_1^-, X_2^-, \cdots, X_m^-\}$;

Step 2.2.4: Calculate vectors X^-X^+ and X_i formed by X^+ $X^-$and vectors X^-X_i and X_iX^+ formed by X^+ X^- respectively;

Step 2.2.5: According to (6) and (7), calculate the projection values $prj_{X^-X^+}(X^-X_i)$ and $prj_{X_iX^+}(X^-X^+)$ from vector X^-X_i , vector X^-X^+ and vector X^-X^+ to vector X_iX^+ respectively;

Step 2.2.6: Calculate the relative closeness between scheme X_i and the ideal scheme according to (8);

Step 2.2.7: Sort relative closeness degree (from large to small), and select the scheme with the maximum closeness degree as the optimal scheme.

3. Five Forces Model of Computational Power

3.1 Selection of Computational Power Measurement Indicators

Computational power is the ability of servers in a data center to output results after data processing. It is a comprehensive indicator to measure the computational power of a data center. A higher value indicates a stronger comprehensive computational power [16]. On a server main-board, data is transferred from the CPU [17], memory, hard disk, and NIC in sequence. If graphics processing is needed, GPU [18] is also required. In a broad sense, computational power is a comprehensive concept including computing, storage, transmission (network) and many other connotations. Computational power is a comprehensive index to measure the computational power of data centers [19].

Computational power is determined by three metrics: data processing capacity, data storage capacity, and data circulation capacity. The computational power of a data center is determined by data processing capability, data storage capability and data circulation capability. In the process of responding to the industrial trend of the new generation of digital technology represented by big data and AI [20], data processing capability can be divided into general computational power represented by CPU and intelligent computational power represented by GPU and AI chip. The former is mainly used to perform general tasks, while the latter mainly undertakes computationally intensive tasks such as graphics display, big data analysis, signal processing, artificial intelligence and physical simulation. In summary, this paper selects five metrics for computational power evaluation, namely: general computational power, intelligent computational power, computational efficiency, network capacity, and storage capacity.

General computational power: General computational power refers to the general computational power represented by CPU. In this paper, the average floating point operations per second (FLOPS) of single rack is used to evaluate general computational power output by CPU in the data center, and the unit is TFLOPS (FP32). CPU chips are divided into a variety of architectures, including x86, ARM and so on.

$$CP_{General} = \sum(a_i \times CPU_i) \tag{9}$$

$CP_{General}$ stands for general computational power of the data center;
a_i indicates the number of CPU servers of a certain type;
CPU_i indicates the computational power of this type of CPU server.

Intelligent computational power: The intelligent computational power mainly refers to the intelligent computational power represented by GPU and AI chip. In this paper, the average floating point operations per second (FLOPS) of single rack is used to evaluate intelligent computational power output by GPU and AI chips in the data center, and the unit is TFLOPS (FP32).

$$CP_{Intelligent} = \sum(b_i \times GPU_i + c_i \times FPGA_i + d_i \times ASIC_i) \tag{10}$$

$CP_{Intelligent}$ stands for intelligent computational power of the data center;
b_i indicates the number of GPU servers of a certain type;
c_i indicates the number of FPGA servers of a certain type;
d_i indicates the number of ASIC servers of a certain type;
GPU_i indicates the computational power of this type of GPU server;
$FPGA_i$ indicates the computational power of this type of FPGA server;
$ASIC_i$ indicates the computational power of this type of ASIC server.

Computational efficiency: Computational efficiency (CE) refers to the ratio of computational power to the power consumption of all IT devices. IT is an efficiency that considers both computational performance and power of the data center. The computational efficiency unit in this paper is GFLOPS/W (FP32).

$$CE = \frac{CP}{\sum IT\ equipment\ power} \tag{11}$$

CP stands for computational power, which is the sum of general computational power and intelligent computational power.$\sum IT\ equipment\ power$ indicates the sum of the power of all IT devices in the data center. In (11), the calculation efficiency represents the computational power generated by the power consumption per watt of the IT equipment in the data center.

Network capability: There are many indicators to measure network capability. In this paper, network bandwidth speed is used to measure network performance. The unit is Mbit/s (Megabits per second), that is, the number of bits transmitted per second.

Storage capability: Storage capability is determined by storage capacity, storage performance, and storage security. This section uses input/output operations per second (IOPS) to measure storage performance, which is the read/write times per second.

3.2 Model Construction

In this section, the measurement information of data center is combined with the bidirectional projection model, and a decision model is given to process the information of different indexes of computational power in different data centers by using bidirectional projection method, and construct "Five Forces Model of Computational Power". An example is analyzed to show that the decision model has good effect. The specific steps of the model are as shown below:

Step 3.2.1: The indicators are graded according to the data. Maximize and minimize existing data. In the middle of the maximum value and minimum value, according to the number of grades required isometric division. In general, the more desirable the value, the higher the grade value.

Step 3.2.2: Grade the data and convert it into a real number (between 0 and 1) of superior order. According to the ranking number table divided in Step 3.2.1, The corresponding grade number is determined according to the data under each index. In each index, the grades of different data centers are compared in pairs, and the grades of one data center are better or worse than another data center in one index. Through the calculation formula of the superior ordinal number, the number of each grade is converted to 0-1, which is convenient for subsequent processing.

Step 3.2.3: Determine X^+ and X^- and determine the corresponding vectors by calculation according to Definition 4. It is necessary to take the maximum and minimum value of the corresponding optimal ordinal number under each index to obtain the X^+ and X^- under this index. Calculate the corresponding vector by (3).

Step 3.2.4: Each vector is obtained by computing model, we get $cos(X^-X_i, X^-X^+)$, $cos(X^-X_i, X^-X^+)$ and other data. According to (6) and (7), the corresponding vector $X^-X_i$to vector X^-X^+, and the projection value of vector X^-X^+ to vector X_iX^+ are calculated respectively for each data center.

Step 3.2.5: calculating the relative closeness of each data center from (8).

Step 3.2.6: Sort the size according to the value of relative closeness. Star rating is performed for each data center according to the relative proximity value and the star rating table. Finally draw a conclusion.

4. Case Study

Table 1 shows the five indicators (general computational power, intelligent computational power, computational efficiency, network capability and storage capability) corresponding to the six data centers.

Table 1. Sample data

Serial number	General computational power (Unit: TFLOPS)	Intelligent computational power (Unit: TFLOPS)	Computational efficiency (Unit: GFLOPS/W)	Network capability (Unit: Mbit/s)	Storage capability (Unit: IOPS)
DC.1	61.25	547.23	72	901	8.1
DC.2	137.3	545.03	40.3	1699.3	12.7
DC.3	23.9	50.61	23.9	1218.4	3.6
DC.4	20.2	350.32	100	964.9	15.4
DC.5	127.07	640.65	80.44	376.3	3.3
DC.6	16.65	88.35	13.24	467.6	4.5

Based on the experience of experts and data distribution, the evaluation steps are as follows: Step 4.1.1: Classify the five indicators according to the data, as shown below;

Table 2. Classification of five forces index of data center computational power

Serial number	Level1	Level2	Level3	Level4	Level5
General computational power (Unit: TFLOPS)	0-10	10-20	20-50	50-100	100-200
Intelligent computational power (Unit: TFLOPS)	0-90	90-130	130-230	230-500	500-1000
Computational efficiency (Unit: GFLOPS/W)	0-10	10-20	20-30	30-50	50-100
Network capability (Unit: Mbit/s)	0-300	300-500	500-900	900-1500	1500-2200
Storage capability (Unit: IOPS)	0-1	1-3	3-7	7-12	12-20

Step 4.1.2: Grade the data in **Table 1** according to the data center computational power index classification table in **Table 2**. Under each index, compare the grades of each data center in pairs to obtain the relative grades and convert them into superior numbers, as shown in **Table 3**, **Table 4** and **Table 5**.

Table 3. Data center computational power index grading

Serial number	General computational power	Intelligent computational power	Computational efficiency	Network capability	Storage capability
DC.1	4	5	5	4	4
DC.2	5	5	4	5	5
DC.3	3	1	3	4	3
DC.4	3	4	5	4	5
DC.5	5	5	5	2	3
DC.6	2	1	2	2	3

Table 4. Pairwise comparison of different indicators in different data centers

Serial number	General computational power	Intelligent computational power	Computational efficiency	Network capability	Storage capability
DC.1	$[r_0,r_{-1},r_1,r_1,r_{-1},r_2]$	$[r_0,r_0,r_4,r_1,r_0,r_4]$	$[r_0,r_1,r_2,r_0,r_0,r_3]$	$[r_0,r_{-1},r_0,r_0,r_2,r_2]$	$[r_0,r_{-1},r_1,r_{-1},r_1,r_1]$
DC.2	$[r_1,r_0,r_2,r_2,r_0,r_3]$	$[r_0,r_0,r_4,r_1,r_0,r_4]$	$[r_{-1},r_0,r_1,r_{-1},r_{-1},r_2]$	$[r_1,r_0,r_1,r_1,r_3,r_3]$	$[r_1,r_0,r_2,r_0,r_2,r_2]$
DC.3	$[r_{-1},r_{-2},r_0,r_0,r_{-2},r_1]$	$[r_{-4},r_{-4},r_0,r_{-3},r_{-4},r_0]$	$[r_{-2},r_{-1},r_0,r_{-2},r_{-2},r_1]$	$[r_0,r_{-1},r_0,r_0,r_2,r_2]$	$[r_{-1},r_{-2},r_0,r_{-2},r_0,r_0]$
DC.4	$[r_{-1},r_{-2},r_0,r_0,r_{-2},r_1]$	$[r_{-1},r_{-1},r_3,r_0,r_{-1},r_3]$	$[r_0,r_1,r_2,r_0,r_0,r_3]$	$[r_0,r_{-1},r_0,r_0,r_2,r_2]$	$[r_1,r_0,r_2,r_0,r_2,r_2]$
DC.5	$[r_1,r_0,r_2,r_2,r_0,r_3]$	$[r_0,r_0,r_4,r_1,r_0,r_4]$	$[r_0,r_1,r_2,r_0,r_0,r_3]$	$[r_{-2},r_{-3},r_{-2},r_{-2},r_0,r_0]$	$[r_{-1},r_{-2},r_0,r_{-2},r_0,r_0]$
DC.6	$[r_{-2},r_{-3},r_{-1},r_{-1},r_{-3},r_0]$	$[r_{-4},r_{-4},r_0,r_{-3},r_{-4},r_0]$	$[r_{-3},r_{-2},r_{-1},r_{-3},r_{-3},r_0]$	$[r_{-2},r_{-3},r_{-2},r_{-2},r_0,r_0]$	$[r_{-1},r_{-2},r_0,r_{-2},r_0,r_0]$

Table 5. Transformation table of superior Ordinal Numbers for comparison of data center levels

Serial number	General computational power	Intelligent computational power	Computational efficiency	Network capability	Storage capability
DC.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]
DC.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]
DC.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]
DC.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]
DC.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]
DC.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 4.1.3: Determine X^+ and X^-, and calculate and determine the corresponding vectors;

$X^+ = \{[0.57,0,0.67,0,0.8],[0,0,1,0.57,0,1],[0,0.57,0.67,0,0,0.8],,$
$[0.57,0,0.57,0.57,0.8,0.8],[0.57,0,0.67,0,0.67,0.67]\};$

$X^- = \{[-0.67,-0.8,-0.57,-0.57,-0.8,0],[-1,-1,0,-0.8,-1,0],$
$[0.8,0.67,-0.57,0.8,0.8,0],[-0.67,-0.8,-0.67,-0.67,0,0],$
$[-0.57,-0.67,0,-0.67,0,0]\};$

$X^-X^+ = \{[0.8,1.24],[1,1.37],[0.8,1.24],[0.8,1.24],[0.67,1.14]\};$

$X^-X_1 = \{[0.23,1.14],[1,1.37],[0.8,1.24],[0.23,0.67],[0.10,0.57]\};$

$X_1X^+ = \{[0.10,0.57],[0,0],[0,0],[0.13,0.57],[0.10,0.57]\};$

$X^-X_2 = \{[0.8,1.24],[1,1.37],[0.23,1.14],[0.8,1.24],[0.67,1.14]\};$

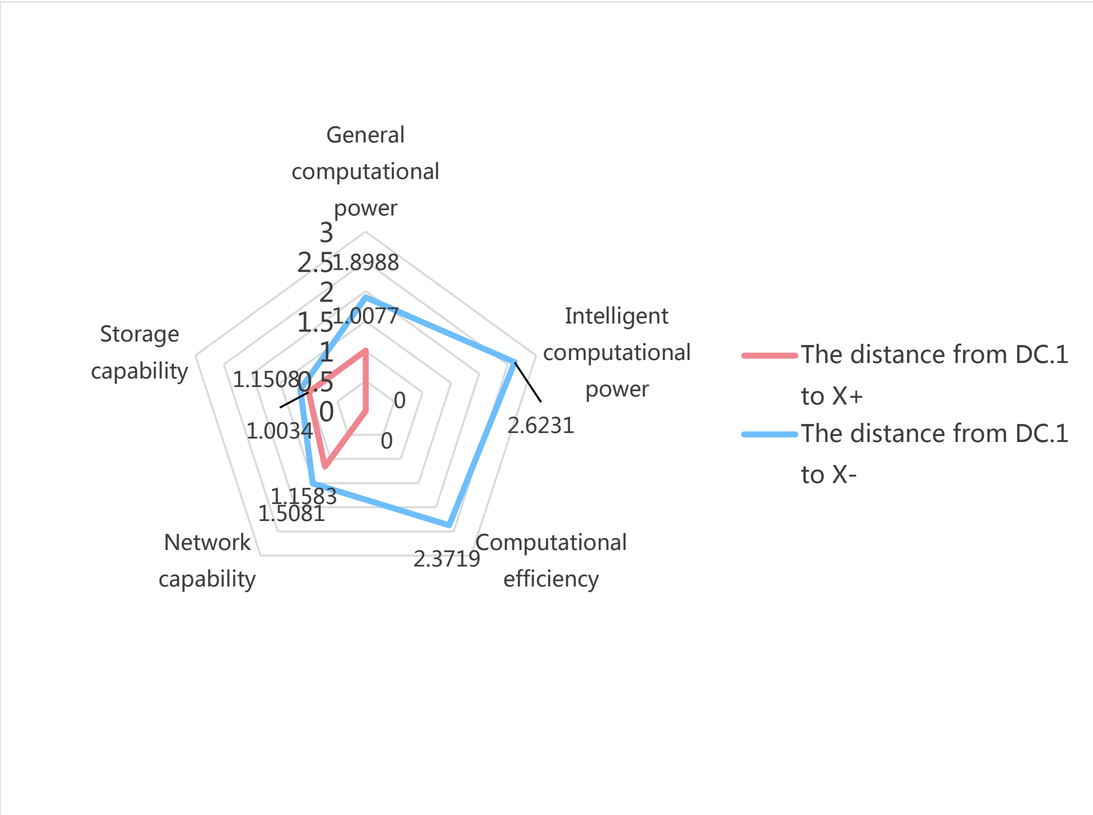
$X\ _2X^+ = \{[0,0],[0,0],[0.10,0.57],[0,0],[0,0]\};$

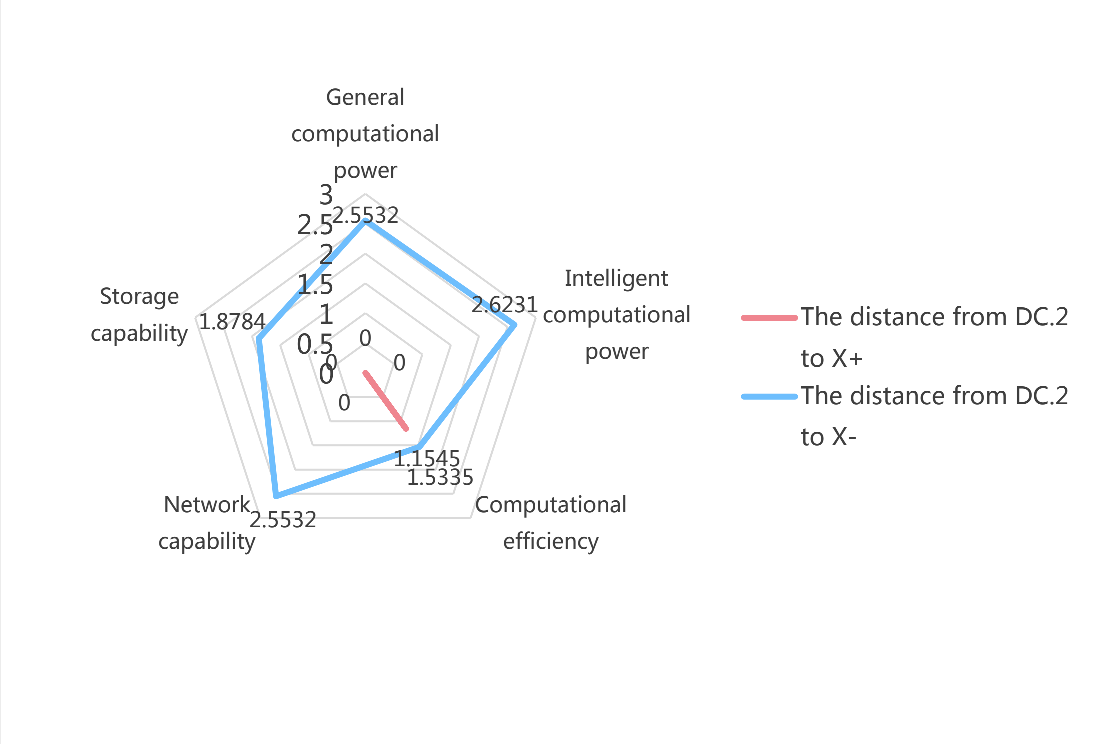
$X^-X_3 = \{[0.10,0.57],[0,0],[0.10,0.57],[0.23,0.67],[0,0]\};$

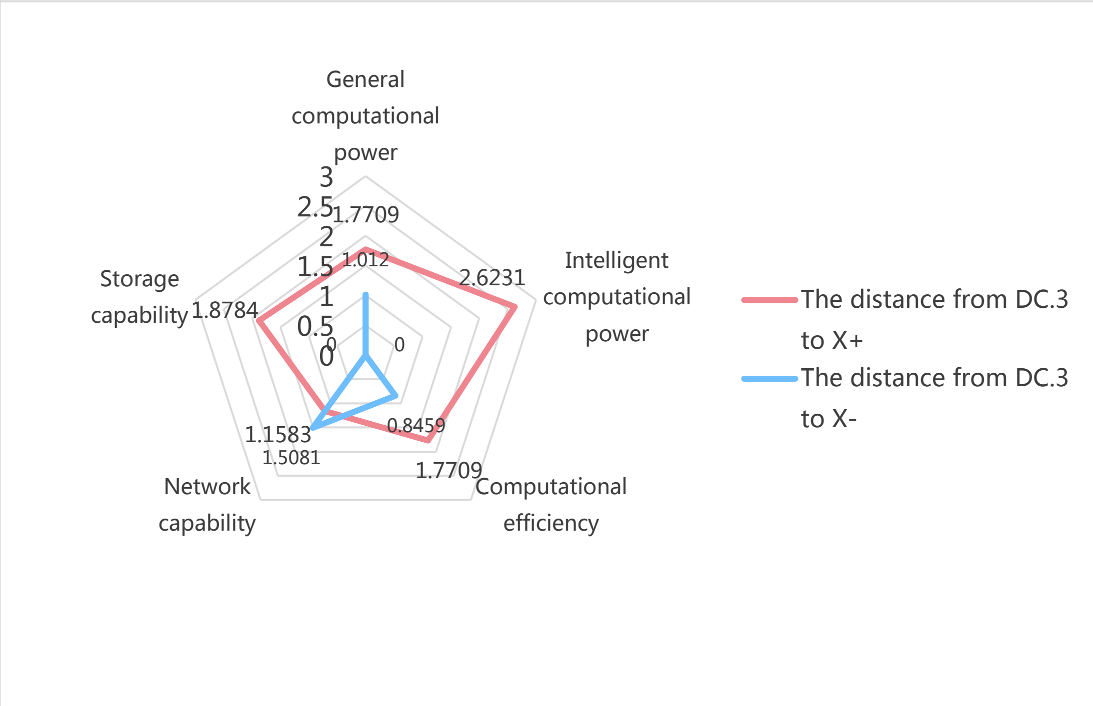
$X_3X^+ = \{[0.23,1.14],[1,1.37],[0.23,1.14],[0.13,0.57],[0.67,1.14]\};$

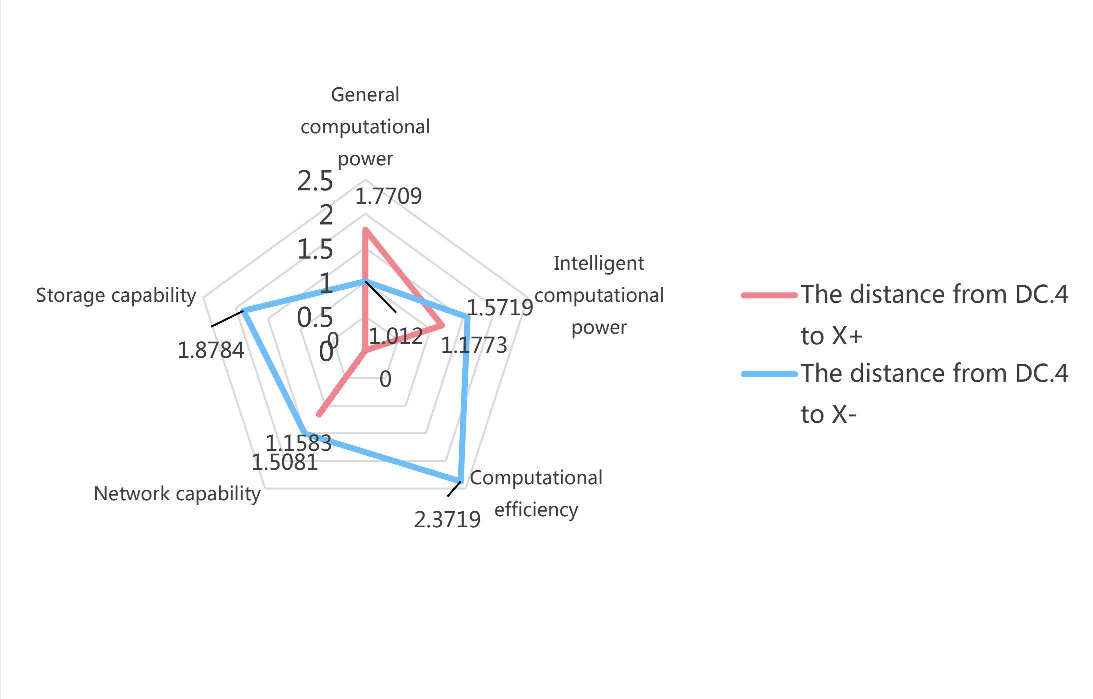
$X^-X_4 = \{[0.10,0.57], [0.43,0.8], [0.8,1.24], [0.23,0.67], [0.67,1.14]\};$
$X_4X^+ = \{[0.23,1.14], [0.2,0.57], [0,0], [0.13,0.57], [0,0]\};$
$X^-X_5 = \{[0.8,1.24], [1,1.37], [0.8,1.24], [0,0], [0,0]\};$
$X_5X^+ = \{[0,0], [0,0], [0,0], [0.8,1.24], [0.67,1.14]\};$
$X^-X_6 = \{[0,0], [0,0], [0,0], [0,0], [0,0]\};$
$X_6X^+ = \{[0.8,1.24], [1,1.37], [0.8,1.24], [0.8,1.24], [0.67,1.14]\}.$

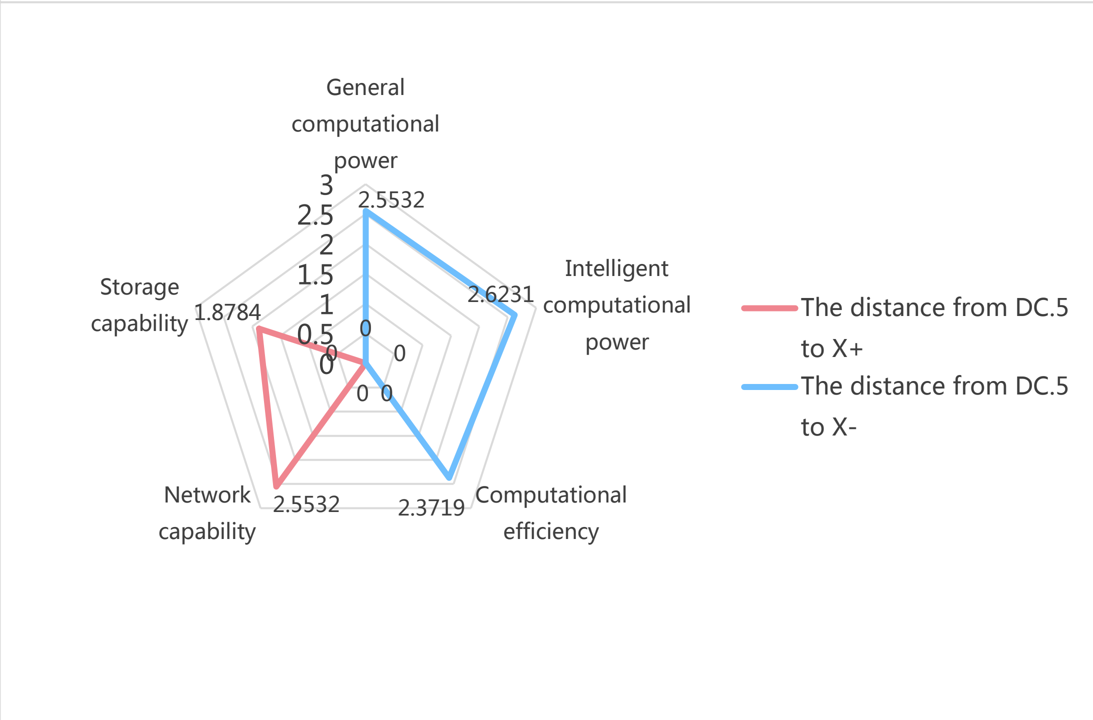
In **Fig. 2**, the red coil represents the distance between each indicator of each data center and X^+. If the red coil is smaller, it indicates that the data center is closer to X^+ of each indicator, and the data center is better, otherwise the opposite. The blue coil represents the distance of each metric for each data center relative to X^-. The larger the blue coil is, the farther the index of the data center is from X^-, the better the data center is, otherwise the opposite. In **Fig. 2**, we can intuitively see that DC.6 is the worst overall, while DC.1 and DC.2 are relatively better.




General computational power
Intelligent computational power
Computational efficiency
Network capability
Storage capability
3
2.5
2
1.5
1
0.5
0
2.5532
2.6231
1.1545
1.5335
2.5532
1.8784
0
0
0
0
The distance from DC.2 to X+
The distance from DC.2 to X-


General computational power
Intelligent computational power
Computational efficiency
Network capability
Storage capability
3
2.5
2
1.5
1
0.5
0
1.7709
1.012
2.6231
0
0.8459
1.7709
1.1583
1.5081
1.8784
0
The distance from DC.3 to X+
The distance from DC.3 to X-


General computational power
Intelligent computational power
Computational efficiency
Network capability
Storage capability
2.5
2
1.5
1
0.5
0
1.7709
1.012
1.5719
1.1773
2.3719
1.1583
1.5081
1.8784
The distance from DC.4 to X+
The distance from DC.4 to X-


General computational power
Intelligent computational power
Computational efficiency
Network capability
Storage capability
3
2.5
2
1.5
1
0.5
0
2.5532
2.6231
2.3719
2.5532
1.8784
The distance from DC.5 to X+
The distance from DC.5 to X-

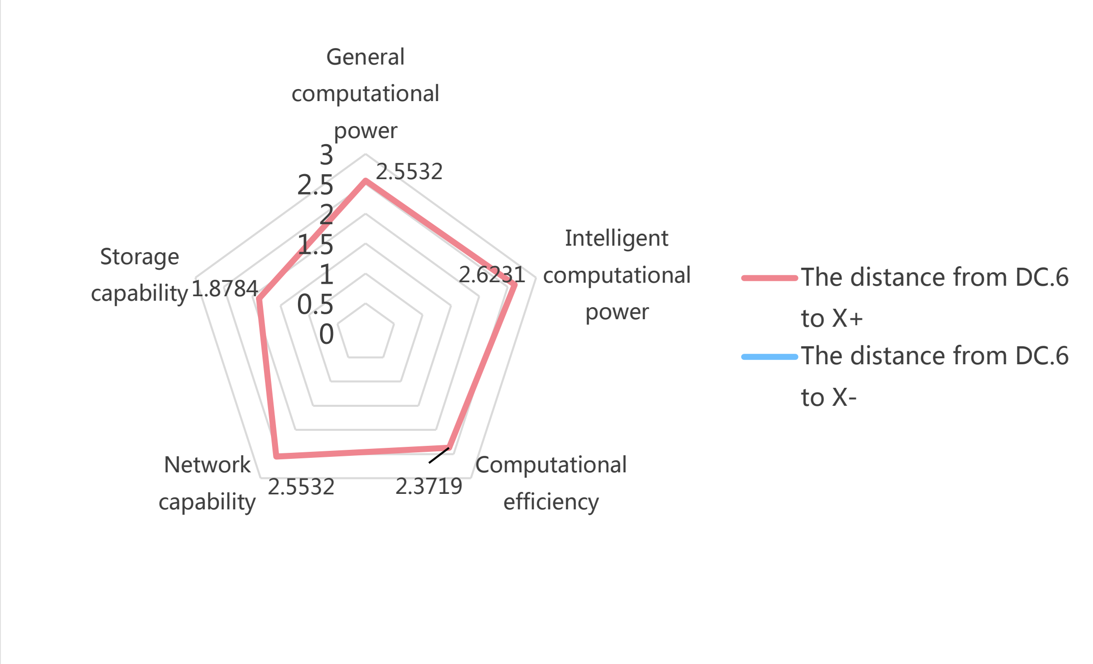


Fig. 2. DC.1-DC.6 Distance between each index and positive and negative ideal schemes

Step 4.1.4: Calculate the corresponding projection value;

Corresponding modules are obtained as follows:

$|X^{-}X^{+}| \approx 3.3392$; $|X^{-}X_1| \approx 2.6915$; $|X_1X^{+}| \approx 1.0077$; $|X^{-}X_2| \approx 3.2149$; $|X_2X^{+}| \approx 0.5793$; $|X^{-}X_3| \approx 1.0807$; $|X_3X^{+}| \approx 2.7735$; $|X^{-}X_4| \approx 2.3621$; $|X_4X^{+}| \approx 1.4385$; $|X^{-}X_5| \approx 2.6882$; $|X_5X^{+}| \approx 1.9808$; $|X^{-}X_6| \approx 0$; $|X_6X^{+}| \approx 3.3392$.

Here, the modulus obtained by each data center (overall distance from positive and negative ideal schemes) is drawn into **Fig. 3** In the figure, the closer the data center corresponding to the red coil is to the central position, the closer the overall distance of the data center is to X^{+}, and the better the overall situation is, and vice versa. The closer the data center in the blue circle is to the extents of the diagram, the farther the data center is from X^{-}, and the better the overall situation is, and vice versa. It can be seen intuitively that DC.1, DC.2, DC.4, DC.5 are relatively good, while DC.3, DC.6 are relatively poor, which coincides with the final conclusion.

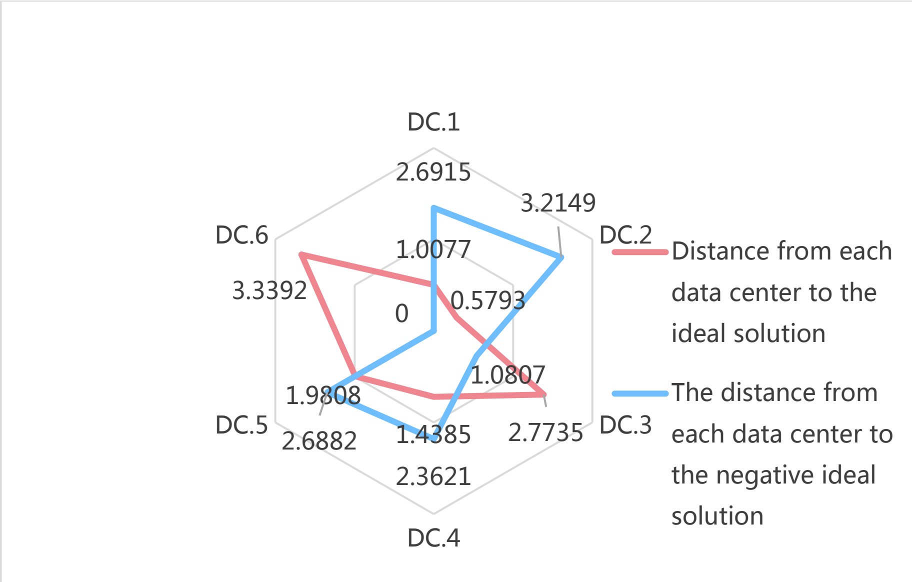


Fig. 3. Distance between sample data and positive and negative ideal schemes

Then the projection value is obtained as follows:

$$Pr\,j_{X^-X^+}(X^-X_1) \approx 2.5085;\ Pr\,j_{X_1X^+}(X^-X^+) \approx 2.2966;$$
$$Pr\,j_{X^-X^+}(X^-X_2) \approx 3.1669;\ Pr\,j_{X_2X^+}(X^-X^+) \approx 1.3528;$$
$$Pr\,j_{X^-X^+}(X^-X_3) \approx 0.7713;\ Pr\,j_{X_3X^+}(X^-X^+) \approx 3.1156;$$
$$Pr\,j_{X^-X^+}(X^-X_4) \approx 2.1685;\ Pr\,j_{X_4X^+}(X^-X^+) \approx 2.3606;$$
$$Pr\,j_{X^-X^+}(X^-X_5) \approx 2.1642;\ Pr\,j_{X_5X^+}(X^-X^+) \approx 1.9808;$$
$$Pr\,j_{X^-X^+}(X^-X_6) = 0;\qquad Pr\,j_{X_6X^+}(X^-X^+) \approx 3.3391.$$

Step 4.1.5: Calculate the relative closeness degree of each data center;

$$C(DC.1) \approx 0.5220;\ C(DC.2) \approx 0.7007;\ C(DC.3) \approx 0.1984;$$
$$C(DC.4) \approx 0.4788;\ C(DC.5) \approx 0.5221;\ C(DC.6) = 0.$$

Step 4.1.6: Sort the size according to the value of relative closeness, determine the star rating of each data center according to **Table 6**, and finally draw a conclusion.

Table 6. Corresponding table of relative closeness degree and star rating

Relative closeness	**0-0.15**	**0.15-0.30**	**0.30-0.50**	**0.50-0.70**	**0.70-1.0**
Level	★	★★	★★★	★★★★	★★★★★

Based on the calculated relative closeness with **Table 7**, the corresponding star rating for each data center is derived as follows.

Table 7. Data Center Class Comparison Table

Data center	**Level**
DC.1	★★★★
DC.2	★★★★★
DC.3	★★
DC.4	★★★
DC.5	★★★★
DC.6	★

5. Conclusion

As an important capability of data center, computational power supports the development of application scenarios such as artificial intelligence, IoT and AR/VR. Meanwhile, the rapid popularization of these application scenarios also needs higher level of computational power in data center. Computational power is affected by computational, network, storage and power consumption. If it cannot be comprehensively measured, it cannot be improved. Consequently, it is particularly significant to thoroughly evaluate the computational power of data center.

Based on the research on computational power of data center, the "five forces model" is proposed. Firstly, the data center is divided into numerical grades in general computational power, intelligent computational power, computational efficiency, network capability and storage capability. Secondly, the bidirectional projection method and TOPSIS method are used to calculate each data center. Finally, star rating is made for different data centers by comparing the relative proximity value. The model makes the results more differentiated and reflects the advantages and disadvantages of different data centers more truly. However, the method proposed in this paper does not consider such factors as data measurement error and whether there is a fixed proportion between different indicators to make the overall efficiency better, which will be explored in future studies.

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