



OPEN Double weighted combat data quality evaluation method based on CVF optimized FAHP

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During multi-agent combat simulation exercises, accurately assessing the quality of collected combat data is a critical step. Addressing the current issue of low accuracy in combat data quality evaluation, which fails to effectively support simulation exercises, this paper proposes a Double-Weighted FAHP optimized by CVF (comparative value function) method for assessing combat data quality. First, a three-tiered evaluation framework for combat data quality indicators is established, with threshold values determined for each indicator. The weights obtained from the FAHP method are optimized using the Satisfaction Consistency Approach to derive the first-tier weights. Subsequently, the CVF is constructed to obtain the second-tier weights. The double-weighted evaluation theory combines these two tiers of weights to produce the final assessment. Analysis of the experimental results indicates that the proposed method reduces the mean squared error to 5.35 when compared to results obtained using FAHP, interval intuitionistic fuzzy methods, and artificial neural networks, bringing it closer to actual standard values. This method provides a more accurate evaluation of the quality of multi-agent combat data, offering robust data support for future combat simulation exercises and military drills.

Keywords Combat data, Fuzzy analytic hierarchy process, Comparison value function, Double weighted, Satisfactory consistency

In recent years, the theory of nonlinear and complex adaptive systems has developed rapidly¹. Various research teams and departments have developed combat simulation systems based on this theory, which better reflect the characteristics of nonlinearity and complexity among individuals in combat. This has opened new avenues for research in modern combat simulation. Compared to general simulation training systems, large-scale simulation systems require significantly higher standards of data accuracy and reliability. The quality of the data directly impacts the series of applications or decision-making processes based on simulation results. An inaccurate simulation outcome could lead to critical decision-making errors². To a certain extent, ensuring the quality of the data used in simulations is a prerequisite for the credibility of large-scale simulation systems. Only with high-quality data can the simulation results possess practical value, and the large-scale simulation system itself demonstrate its vitality. Given the inherent complexity of military operations or related issues, data quality becomes a particularly critical factor in large-scale military simulation systems. While the importance of model verification, validation, and accreditation (VV&A) has been gradually recognized, research on methods for assessing and improving the quality of data used in these simulations remains limited. With the advent of the information age, the quantity of data has increased exponentially, making it challenging to ensure data quality; thus, the assessment of data quality has become increasingly important³. Combat data, as an input component of combat simulation systems, significantly affects the correctness and rationality of the output results. Currently, there is no universally accepted definition of data quality. The U.S. National Information System Dictionary defines data quality as “the degree to which data is suitable for user application, including attributes such as accuracy, timeliness, precision, completeness, relevance, and expressiveness”. The quality of simulation data is influenced and constrained by a variety of factors, making it necessary to quantify these factors when evaluating data quality⁴. A data quality evaluation index system refers to a set of interrelated metrics designed to achieve a specific research objective. Its establishment not only requires identifying which influencing factors constitute the evaluation system but also determining the relationships among these metrics, i.e., the structure of the index system. The primary goal of evaluating data quality in a simulation system is to comprehensively understand the overall state of data quality. Therefore, it is essential to assess the quality of combat data. In contemporary modern warfare, a plethora of combat data emerges, with useful and useless data intermixed, leading to challenges in

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ensuring quality. A scientific and rational assessment of this data can enhance combat planning and improve the decision-making capabilities of commanders⁵. Additionally, the evaluation of combat data quality plays a crucial role in refining operational plans and optimizing command decisions.

Currently, many research outcomes have emerged regarding the assessment of combat data quality. In combat data quality evaluation, hierarchical analysis methods are commonly used to establish a certain hierarchical structure. Within such structures, determining the weights of various indicators related to combat data quality is particularly crucial. The primary methods for calculating indicator weights include the following:

(1) Subjective weighting methods.

Common subjective weighting methods include FAHP⁶, expert survey methods⁷, G1 method⁸, and ratio comparison scoring methods⁹. Among these, FAHP and expert surveys are the two most commonly used methods, which are detailed below.

FAHP: FAHP is one of the commonly used subjective weighting methods. It is developed from the Analytic Hierarchy Process (AHP)¹⁰ and serves as a hierarchical weight decision analysis method¹¹. In FAHP, fuzzy sets replace the data in the judgment matrix of AHP, allowing for the calculation of fuzzy weights for each element. The core idea is to quantitatively handle qualitative issues and to structure problems hierarchically. FAHP requires the establishment of a hierarchical system for the attributes, where upper-level attributes influence lower-level attributes. However, FAHP has its limitations; if the hierarchy is constructed improperly or the weight values are set inappropriately, it can adversely affect the final decision outcome.

Expert Survey Method: Also known as the Delphi method, proposed by Gordon and Helmer, this method aims to avoid the tendency for individuals to blindly follow the majority or yield to authority. In the expert survey method, experts assess various proposed indicators and determine their respective weight values. Throughout the process, the experts do not communicate with each other and independently provide their opinions. The results are then aggregated to derive a final conclusion. However, this method is complex and time-consuming, resulting in poor real-time applicability.

(2) Objective weighting methods.

In subjective weighting methods, weight values are derived from the experts' experiences, lacking a data-driven formula, which affects objectivity. Objective weighting methods address this issue. Currently, objective weighting methods mainly include the entropy method¹², principal component analysis¹³, maximum deviation method (MDM)¹⁴, and multi-objective programming¹⁵, among others. Among these, the entropy method and maximum deviation method are the two most commonly used. The reliability of weights obtained through objective weighting methods is generally higher, as they are based on actual decision data and utilize mathematical methods to construct weighting formulas, allowing for the determination of weight values through these formulas¹⁶.

In the study of data quality assessment methods, in addition to subjective and objective weighting methods, many researchers have proposed various alternative approaches. For instance, Liu L J¹⁷ constructed a six-tuple evaluation model that combines rough set theory with BP neural network theory for assessing the quality of combat data. He W H¹⁸ proposed a comprehensive data quality assessment model that integrates supervised pattern recognition with BP neural networks. This assessment method enhances the accuracy of data evaluation and reduces errors; however, it requires a large volume of data, and when the dataset is small, the evaluation results can be significantly compromised. Yang H¹⁹ et al. and colleagues built a three-layer combat data quality indicator assessment model to evaluate the quality of combat data. This model has lower data requirements but is heavily influenced by subjective factors, leading to considerable errors in the results. Han Z J²⁰ et al. proposed a data quality assessment method for large-scale simulation systems that combines both subjective and objective approaches for evaluating combat data quality. This method reduces the influence of subjective factors, but it lacks the definition of thresholds, making it difficult to effectively mitigate the impact of indicator values, resulting in inaccuracies in the evaluation outcomes. Qiu S²¹ et al. proposed a data valuation evaluation method based on analytic hierarchy process, which improved the accuracy of data evaluation. On the foreign side, Irvanizam et al.^{22,23} adopted a multi-criteria decision-making method to conduct quality assessments in health care services and social assistance. Yu G F et al.^{24,25} established a multi-objective decision-making level evaluation optimization model to evaluate the network security situation. However, the attribute information considered by the proposed method is single.

In response to this, and based on relevant literature, this study proposes a combat data quality assessment method using a double-weighted approach based on FAHP optimized by CVF. The structure of this paper is organized as follows. "Fuzzy analytic hierarchy process" Section discusses the theory of FAHP and the method of calculating the weight formula of fuzzy complementary judgment matrix. "FAHP-CVF combat data quality assessment method based on index double weighted" Section identifies key influencing factors and constructs a new combat data quality evaluation index system, and proposes an FAHP optimized by CVF combat data quality evaluation method based on double-weighted of indicators. The thresholds for each indicator are established, and consistency satisfaction optimization is applied to the FAHP-derived weights to obtain the first layer of weights. CVF is then constructed to generate the second layer of weights. The double-weighted evaluation theory is proposed to integrate the first and second layers of weights. "Experimental results and discussion" Section evaluates combat data quality and Pearson correlation coefficient, Spearman correlation coefficient, significance and difference index were used to analyze the results obtained by the four methods. Lastly, "Conclusion" Sect. presents some conclusions of the study.

Fuzzy analytic hierarchy process

FAHP is a research method that combines fuzzy mathematics with the Analytic Hierarchy Process^{26,27}. This method is widely used in the field of determining indicator weights and improves the issues present in traditional Analytic Hierarchy Process, significantly enhancing the reliability of decision-making. The basic idea of FAHP is to decompose the problem into a multi-level structure based on the nature of the evaluation problem^{28,29}. When solving the problem, it mainly involves three steps:

- Establishing a multi-level model and conducting a reasonable analysis of the causal relationships between factors within each level.
- Comparing pairwise the factors within the same level based on the criteria of the previous level to determine their relative importance and construct a fuzzy judgment matrix.
- After calculation, rationalize the ranking of the required alternatives based on the relative importance of each factor, thus providing a rational and scientific decision-making basis for the final decision.

A. Establishment of fuzzy complementary judgment matrix.

In the fuzzy analytic hierarchy process, when pairwise comparisons are required among indicators, a quantitative representation of the relative importance of one factor to another is used, resulting in a fuzzy judgment matrix $A = (a_{ij})_{n \times n}$. It has the following properties:

- $a_{ii} = 0.5, i = 1, 2, \dots, n;$
- $a_{ij} + a_{ji} = 1, i, j = 1, 2, \dots, n;$

This type of judgment matrix is called a fuzzy complementary judgment matrix³⁰. To facilitate the quantitative description of the relative importance of any two indicators with respect to certain criteria, a 0.1 to 0.9 scale method, as shown in Table 1, is adopted to scale the quantities.

According to the above digital index scale, the fuzzy complementary judgment matrix of Formula (1) can be obtained by comparing the index factor $a_1, a_2, \dots, a_n$ in pairs.

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \tag{1}$$

B. Weight formula of fuzzy complementary judgment matrix.

According to the fuzzy complementary judgment matrix, formula (2) can be used to solve the weight of the fuzzy complementary judgment matrix³¹. The weight formula is as follows:

$$W_i = \frac{\sum_j^n a_{ij} + \frac{n}{2} - 1}{n(n-1)}, (i = 1, 2, \dots, n) \tag{2}$$

FAHP-CVF combat data quality assessment method based on index double weighted

The flow chart of combat data quality assessment method based on index double-weighted is shown in Fig. 1.

A. Establish combat data quality index system.

Since combat data is derived from the effective integration of operational data across different systems, it is essential that each subsystem adheres to specific evaluation criteria during data storage, transmission, and

Scale	Define	Instructions
0.5	Equally important	Two indicators are equally important.
0.6	Slightly more important	One indicator is slightly more important than the other when compared
0.7	Significantly more important	One indicator is noticeably more important than the other when compared
0.8	Much more important	One indicator is much more important than the other when compared
0.9	Extremely important	One indicator is extremely more important than the other when compared
0.1 0.2 0.3 0.4	Inverse comparison	If the comparison of indicator a_i and indicator a_j results in judgment r_{ij} , then the judgment r_{ji} obtained by comparing indicator a_j and indicator a_i is $r_{ji} = 1 - r_{ij}$

Table 1. 0.1–0.9 scaling method and its significance.

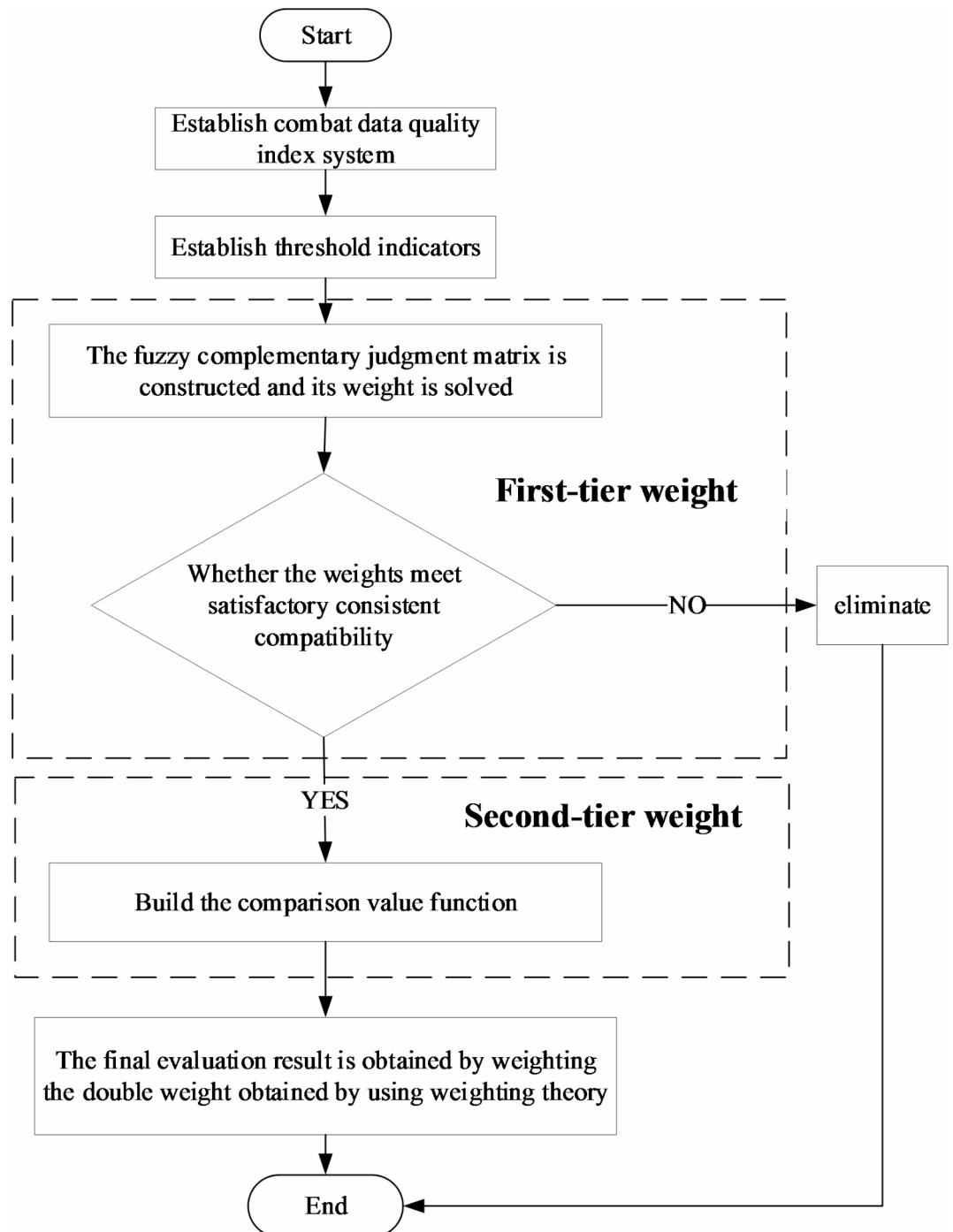


Fig. 1. Flow chart of combat data quality assessment method based on double-weighted.

integration processes to establish a unified standard. This is followed by data cleansing to eliminate irrelevant or faulty data, thereby ensuring the effectiveness and reliability of combat data. The quality of combat data primarily consists of inherent attributes and intrinsic indicators. For the overall assessment of combat data quality, a hierarchical decomposition method is employed, categorizing combat data into three broad types: inherent attributes, expressive attributes, and application attributes. These attributes represent the primary indicators within the combat data quality assessment framework. Specifically, inherent attributes include three secondary indicators: completeness, accuracy, and uniqueness; expressive attributes encompass consistency, timeliness, and understandability; application attributes consist of security, compliance, and stability.

After establishing the combat data quality indicator assessment framework, each indicator is quantitatively processed, allowing all indicators within the framework to be represented by numerical values, referred to as indicator values. The overall structure diagram of the combat data quality indicator system influenced by these indicators is illustrated in Fig. 2.

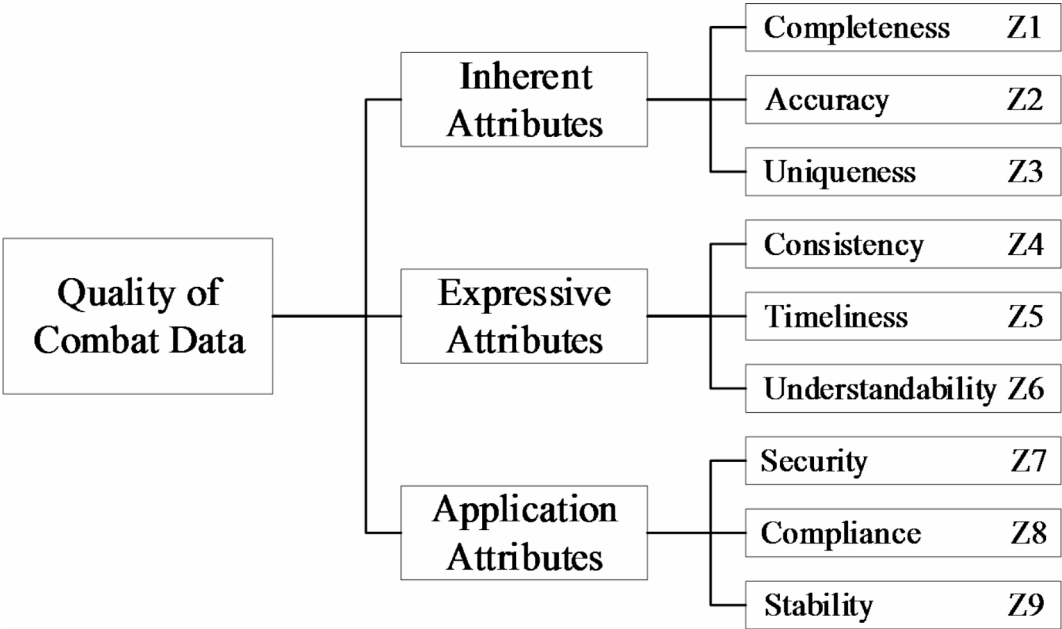


Fig. 2. Quality index system of combat data.

Index	Z ₁	Z ₂	Z ₃	Z ₄	Z ₅	Z ₆	Z ₇	Z ₈	Z ₉
Threshold value	80	95	100	72.8	90	85	92	82	87

Table 2. Indicator threshold table.

In the evaluation study, the threshold indicators are determined by combining the threshold values proposed in reference¹⁷ with the standards that each indicator must meet within the project. Each indicator corresponds to a specific threshold, which is established to assess whether the indicator values meet the minimum standards. The basis for setting these thresholds includes: ① the researcher’s emphasis on specific combat data; ② the reliability of the system being evaluated; ③ the effectiveness of the researchers in analyzing combat data using the dataset; ④ the experience from previous analyses of combat data and conclusions drawn from simulation experiments. The various threshold indicators used are presented in Table 2.

The threshold value corresponding to Z_i represents the lowest standard score that this index should achieve. Z_1 for completeness, Z_2 for accuracy, Z_3 for uniqueness, Z_4 for consistency, Z_5 for timeliness, Z_6 for understandability, Z_7 for security, Z_8 for compliance, and Z_9 for stability.

B. Fuzzy consistent compatibility test.

The weight values obtained from Formula (2) are based on the evaluation results of individual experts and are susceptible to personal subjective factors, resulting in inaccurate final evaluation results. Therefore, it is necessary to summarize and analyze the evaluations of multiple experts to obtain a reasonable evaluation result and eliminate unreasonable evaluation results. Therefore, the method of data fuzzy consistency³² and compatibility³³ is used to test the evaluation results.

When $A = (a_{ij})_{n \times n}$ and $B = (b_{ij})_{n \times n}$ are both fuzzy judgment matrices, formula (3) is used to solve the compatibility index of matrices A and B between them. The formula is shown below:

$$I(A, B) = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n |a_{ij} + b_{ij} - 1| \tag{3}$$

$W_n = (W_1, W_2, \dots, W_n)^T$ is used to represent the weight vector of fuzzy judgment matrix A , and $\sum_{i=1}^n W_i = 1, W_i \geq 0 (i = 1, 2, \dots, n)$, let $W_{ij} = \frac{W_i}{W_i + W_j}, (\forall i, j = 1, 2, 3, \dots, n)$, then the characteristic matrix of judgment matrix A is:

$$W^* = (W_{ij})_{n \times n} \tag{4}$$

To verify the accuracy of the obtained fuzzy complementary judgment matrix, consistency, and compatibility tests are required, which are:

- When $I(A, W^*) \leq \alpha$ is used, it can be shown that the judgment matrix A satisfies satisfactory consistency.
- When $I(A, B) \leq \alpha$ is used, it can be shown that both the judgment matrices A and B satisfy satisfactory compatibility.

Here, α represents the attitude of the decision maker. The smaller the value of α , the higher the requirement for consistency and compatibility of the decision maker for this fuzzy judgment matrix, and α is usually taken as 0.1.

When both conditions (1) and (2) are satisfied at the same time, the average of the $m(m \leq n)$ weight sets that satisfy the conditions can be used as the weight allocation vector for the factor indicators, and the weight vector expression is as follows, where, W_i represents the final weight vector of the first weight.

$$W_i = \frac{1}{n} \sum_{i=1}^m W_i (i = 1, 2, \dots, n) \quad (5)$$

C. Construction of comparison value function.

The comparison function is used to compare the indicator value and threshold, and the comparison value between the indicator value and threshold can be obtained through calculation to control the growth rate of the final weight. The formula for constructing the comparison function g_i is as follows, where x_i represents the index value of i indicators, u_i represents the threshold value of i indicators, s is the adjustment of the growth rate of the comparison value function, t is used to control the maximum value of g_i when the comparison value is greater than the threshold value, and the evaluation result can be closer to the standard value by adjusting s and t .

$$g_i = \begin{cases} 1/e^{|x_i - u_i|^s}, & x_i < u_i \\ 1, & (x_i = u_i) \cap ((x_i > u_i) \text{ and } ((t - 1/e^{|x_i - u_i|^s}) < 0)) \\ 1 + (t - 1/e^{|x_i - u_i|^s}), & \text{and } (x_i > u_i) \cup (t - 1/e^{|x_i - u_i|^s}) \geq 0 \end{cases} \quad (6)$$

This formula is derived based on the characteristics of the Sigmoid function and piecewise function. It represents the following meaning:

- When the indicator value is smaller than the threshold, the larger the difference between them, the smaller the comparison value, which tends to 0; conversely, when the difference is smaller, the comparison value is larger and tends to 1.
- When the indicator value is equal to the threshold or greater than the threshold and the difference between them is small, the comparison value is 1.
- When the indicator value is greater than the threshold, the larger the difference between them, the larger the comparison value, which is greater than 1; and when the difference is smaller, the comparison value tends to 1.

Figure 3 is the formula curve when $s = 1/4$ and $t = 0.5$ in formula (6).

In Fig. 3, the abscissa is the value of $(x_i - u_i)$, indicating the difference between the index value and the threshold, and the ordinate is g_i , indicating the comparison value. It can be seen from Fig. 3 that the function curve conforms to the three criteria for constructing the comparison value function.

D. Double weighted assessment method.

Using formula (7), the final result value G is evaluated by combining the indicator values, weights, and comparison values, with the combat data quality evaluation results as the result value. Where W_{2i} represents the first weight vector of the secondary sub-indicator Z_p , which is obtained through the idea of weight determination using fuzzy analytic hierarchy process by pairwise comparison of indicators and subsequent consistency and compatibility analysis. g_i represents the second weight of the secondary sub-indicator Z_p , which is obtained by comparing the indicator value with the threshold value to obtain a comparison value. When the indicator value is lower than the threshold value, it indicates that it is lower than the minimum standard, and the corresponding second weight will decrease. Conversely, when the indicator value is greater than the threshold value, indicating that it is higher than the minimum standard, the second weight will increase. x_i represents the indicator values corresponding to each indicator Z_i . W_{11} , W_{12} , W_{13} represents the weights corresponding to the inherent attributes, expressive attributes, and application attributes of the primary sub-indicator.

$$G = \left(\sum_{i=1}^3 W_{2i} g_i x_i \right) W_{11} + \left(\sum_{i=4}^6 W_{2i} g_i x_i \right) W_{12} + \left(\sum_{i=7}^9 W_{2i} g_i x_i \right) W_{13} \quad (7)$$

Experimental results and discussion

E. Test data and experimental design.

In the course of actual combat simulation, a lot of combat data will be generated. The different weights of each index that affect the quality of combat data lead to different index scores. The hardware environment for the simulation experiments is a desktop computer with the main configuration being an Intel i7, 2.9 GHz processor. The software testing environment is a 64-bit Windows 10 system, and the simulation software used is Pycharm.

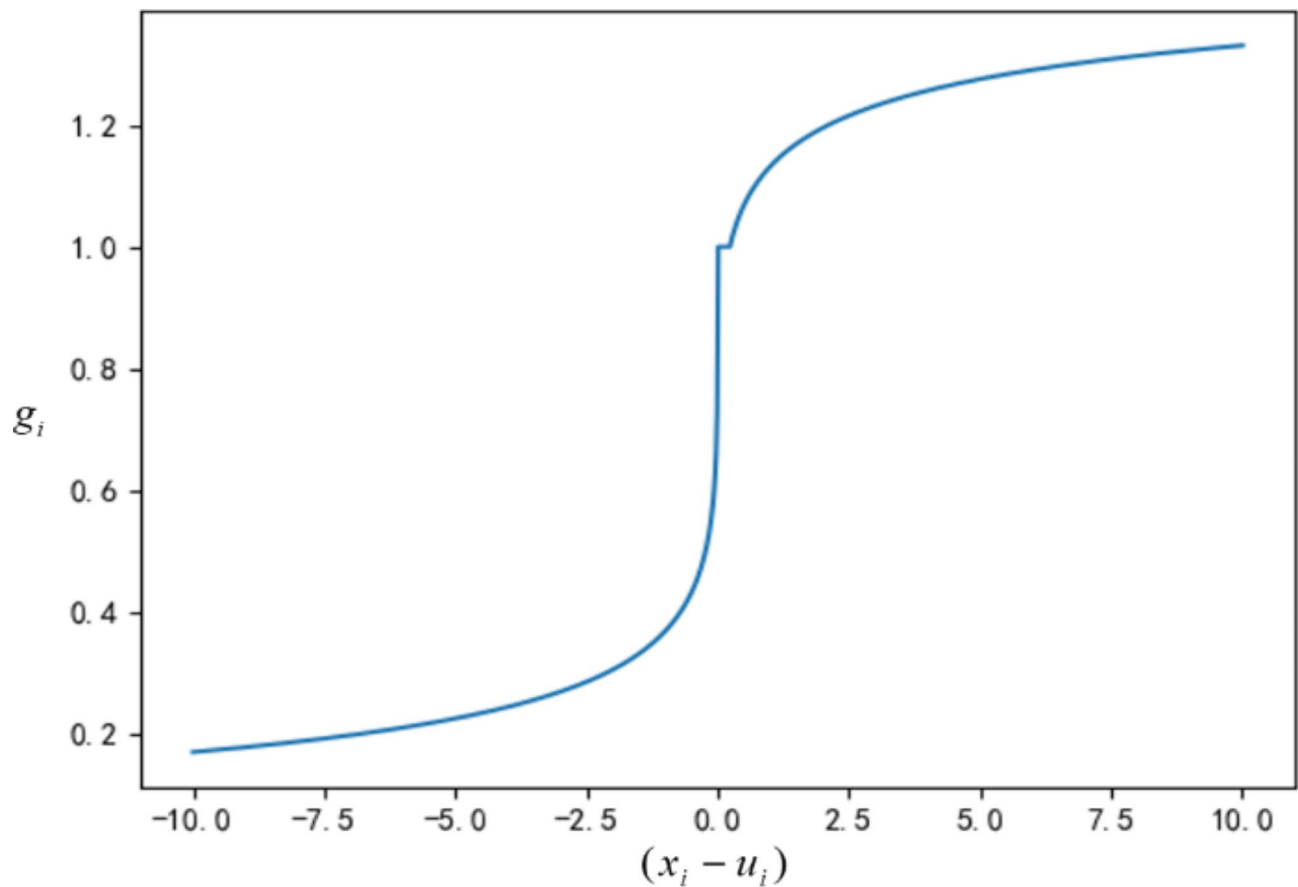


Fig. 3. Comparison value function curve when $s = 1/4$ and $t = 0.5$.

Dataset	M ₁	M ₂	M ₃	M ₄	M ₅	M ₆	M ₇	M ₈
x ₁	96	90	76.5	88.2	82.3	78.6	83.6	91
x ₂	93.4	97.6	96.8	92.8	92.5	93.6	95.6	98.8
x ₃	82	100	100	86	98	92	100	100
x ₄	78.6	92.5	72.3	78.2	75.2	61.6	76	82.4
x ₅	88	95.4	76.8	73.8	42.6	84.6	92.1	95.4
x ₆	78	78.4	89.6	67.8	83.2	83.6	94.6	82.4
x ₇	86.2	92.4	93.4	73	98.6	88.6	77.8	82
x ₈	88.9	89.5	87.4	85.6	83.6	98.2	80.6	91.3
x ₉	86.8	78.8	92.4	84.6	85.2	82.2	95.5	76.6
Evaluation results	49	86	72	41	53	27	91	78

Table 3. Index scoring results and evaluation results. Where x_i represents the corresponding i index value respectively. M_i represents the i group of data.

In this test, 8 groups of data in references¹⁷ were selected, and each index of each data set was synthesized to obtain the corresponding scoring results and evaluation results of the 8 groups of data indicators shown in Table 3.

F. Analysis of simulation results.

The fuzzy analytic hierarchy process is used to compare the indicators pairwise and the fuzzy complementary judgment matrix is obtained using formula (1) are shown in Appendix Table 1.
The weights of the Primary Indicator and Secondary Indicator corresponding to the 8 groups of data obtained by formula (2) are shown in Table 4.
The characteristic matrix corresponding to each group is calculated according to Formula (4), as shown in Appendix Table 2.

Primary Indicator	Secondary Indicator	M ₁	M ₂	M ₃	M ₄	M ₅	M ₆	M ₇	M ₈
W ₁₁ (0.29)	W ₂₁	0.37	0.3	0.27	0.33	0.28	0.3	0.3	0.3
	W ₂₂	0.33	0.33	0.35	0.37	0.34	0.37	0.33	0.33
	W ₂₃	0.3	0.37	0.38	0.3	0.38	0.33	0.37	0.37
W ₁₂ (0.38)	W ₂₄	0.33	0.33	0.3	0.37	0.35	0.27	0.3	0.32
	W ₂₅	0.37	0.37	0.33	0.33	0.25	0.38	0.33	0.36
	W ₂₆	0.3	0.3	0.37	0.3	0.4	0.35	0.37	0.32
W ₁₃ (0.33)	W ₂₇	0.3	0.37	0.37	0.3	0.37	0.33	0.3	0.33
	W ₂₈	0.37	0.33	0.3	0.37	0.3	0.37	0.33	0.37
	W ₂₉	0.33	0.3	0.33	0.33	0.33	0.3	0.37	0.3

Table 4. Index weight table.

Primary Indicator	Secondary Indicator	Final Weight
Inherent Attributes (0.29)	Completeness	0.31
	Accuracy	0.34
	Uniqueness	0.346
Expressive Attributes (0.38)	Consistency	0.32
	Timeliness	0.353
	Understandability	0.33
Application Attributes (0.33)	Security	0.329
	Compliance	0.349
	Stability	0.323

Table 5. Final weighting scale.

Then, formula (3) is used to calculate the pairwise consistency and compatibility of the judgment matrices for each group of data, to analyze whether the pairwise comparisons between each group of data meet satisfactory consistency and compatibility. The results of the analysis are shown in Appendix Tables 3 and 4.

It can be seen from Appendix Table 3 that the values of all indicators in all data sets are less than 0.1, so they all meet satisfactory consistency. Therefore, the weight distribution of these data sets is reasonable.

Based on Appendix Table 4, it is found that only the results of $I(A_{32}, A_{52})$ and $I(A_{52}, A_{72})$ are greater than 0.1, indicating unsatisfactory compatibility. The comparison between the judgment matrices shows that the evaluation data of the fifth group of experts is inaccurate and does not satisfy the satisfactory compatibility when compared with other data. Therefore, it should be removed from the final evaluation.

From Appendix Tables 3 and 4, it is found that except for the evaluation data of the fifth group of experts, all other evaluation data meet the two conditions of satisfactory consistency and satisfactory compatibility. Therefore, using their average as the weight allocation vector of factor indicators is reasonable and reliable. After removing the fifth group of data, the final weight vector is obtained by using the average of the remaining evaluation data in formula (5), as shown in Table 5.

The second weight of the sub-indicators at the second level can be determined using the comparative value function in formula (6). The data from Table 1 is used as the threshold values, and the data from Table 3 is used as the indicator values. Three sets of experimental data are selected with parameters: $s = 1/4, t = 0.5$; $s = 1/4, t = 0.6$; $s = 1/6, t = 0.6$, respectively, to evaluate the comparative values of each second-level sub-indicator. Formula (7) is used to calculate the final evaluation result for the combat data quality. The evaluation results corresponding to each parameter are shown in Fig. 4.

According to Fig. 4, it can be observed that before improvement, the parameter $s = 1/4, t = 0.5$ yields the best evaluation result. Therefore, we select the parameter $s = 1/4, t = 0.5$ to evaluate the test results of the improved second-level sub-indicator data after excluding the fifth set of data. The results are shown in Table 6.

By combining Fig. 4 with Table 6. Comparing their simulation results with the standard values, the comparison results are shown in Fig. 5.

From Fig. 4, it can be observed that different parameter values of s and t lead to different final results. Simulation results always have errors compared to the standard values. By continuously adjusting the parameter s to change the curve's rate of change and adjusting t to limit the maximum value of the second-level weight, the results can be closer to the standard values. From the four sets of comparative simulation results in Fig. 5, it can be seen that, after determining the parameters, the simulation results based on the improved FAHP-CVF method with double-weighted indicators are closer to the standard values in Table 3, with a larger degree of improvement in each data item compared to the results before improvement.

To further validate the proposed method, a comparative analysis was conducted with the BPNN method proposed in reference¹⁸, the FAHP method proposed in reference⁶, and the MDM proposed in reference¹⁴. The reason for selecting BPNN, FAHP, and MDM for comparison is that these three methods are commonly

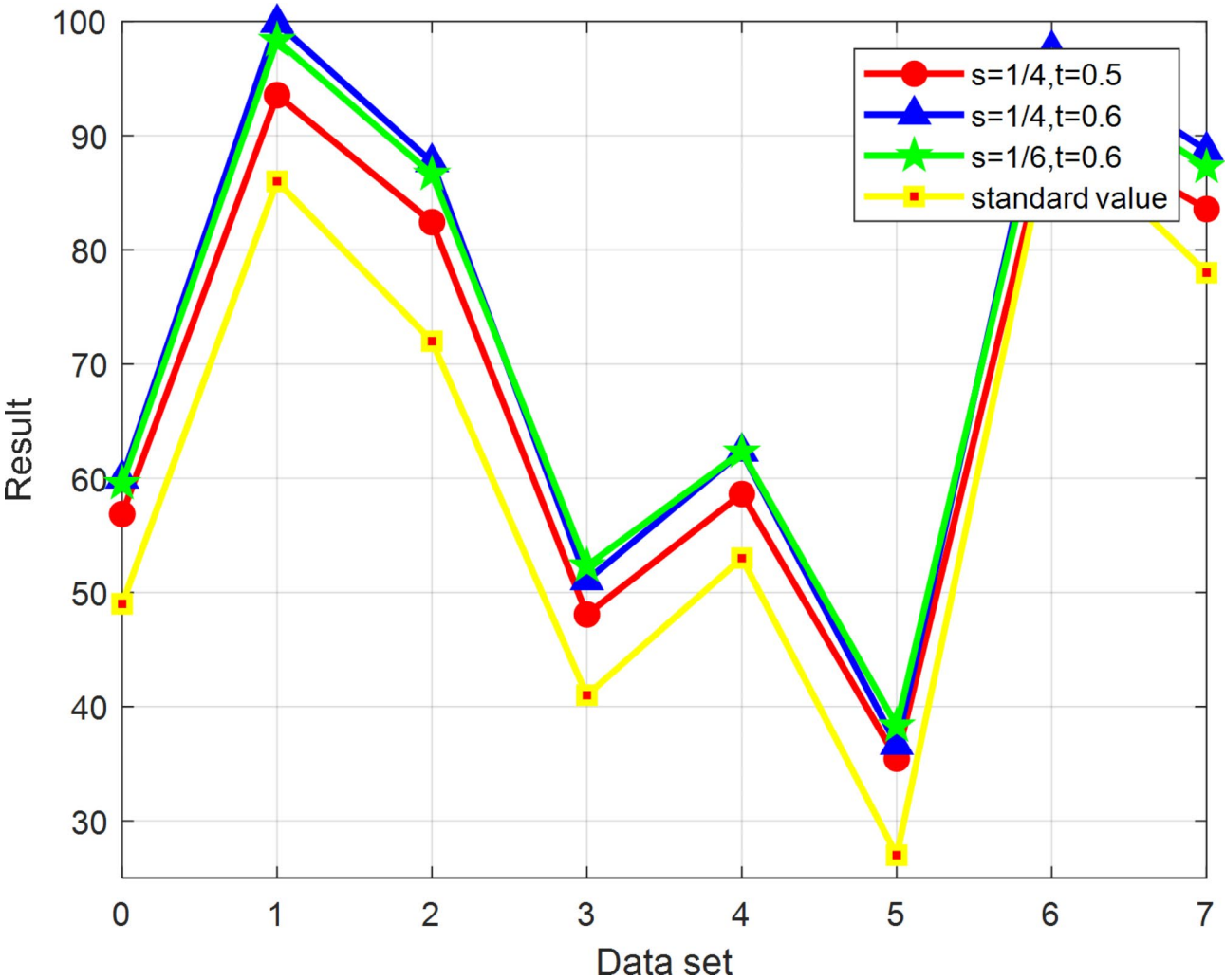


Fig. 4. Comparison of the evaluation results of each parameter.

$s=1/4$ $t=0.5$	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
g_1	1.36	1.33	0.25	1.32	1.21	0.34	1.25	1.34
g_2	0.32	1.22	1.19	0.3	0.28	0.34	1.09	1.25
g_3	0.13	1	1	0.14	0.3	0.19	1	1
g_4	1.29	1.38	0.43	1.28	1.21	0.16	1.24	1.33
g_5	0.3	1.28	0.15	0.13	0.07	0.22	1.2	1.28
g_6	0.2	0.2	1.27	0.13	0.31	0.34	1.33	0.28
g_7	0.21	1.05	1.16	0.12	1.3	0.26	0.14	0.17
g_8	1.3	1.31	1.28	1.25	1.18	1.37	0.34	1.33
g_9	0.51	0.18	1.28	0.29	0.31	0.23	1.32	0.17
Result Value	53.7	91.98	80.01	44.9	57.37	34.33	89.42	82.6

Table 6. Comparison value and result value table after improvement.

used algorithms for data quality assessment, providing accurate and reliable evaluation results. They are suitable for solving practical decision-making problems due to their flexibility and scalability, allowing adjustments and improvements based on specific issues, and BPNN is one of the classical algorithms in machine learning algorithm, FAHP is the representative of classical algorithm in subjective weighting method, MDM is the representative of classical algorithm in objective weighting method. Therefore, comparing the proposed method with these three methods better demonstrates its superiority and general applicability. The comparative results are shown in Fig. 6.

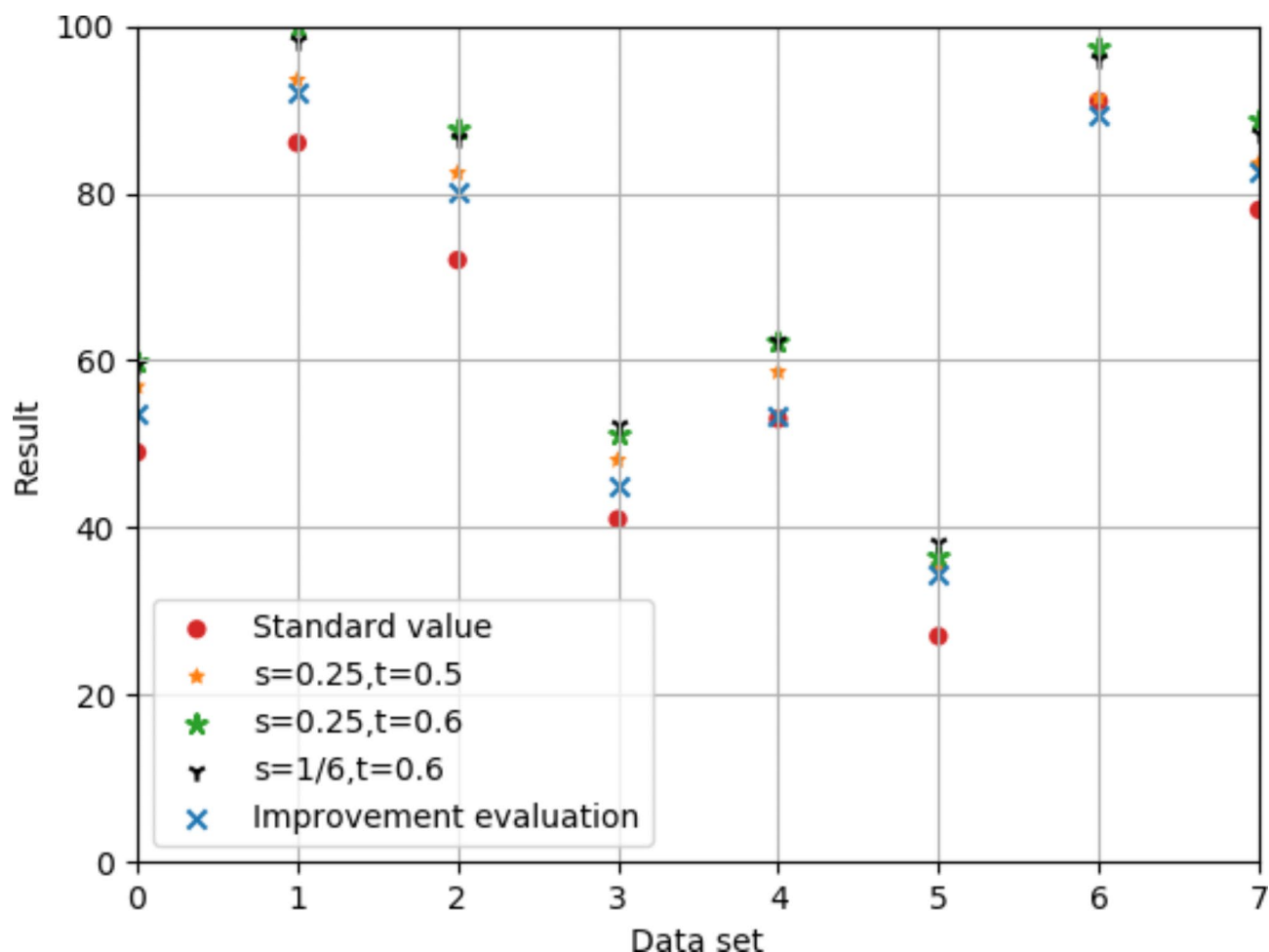


Fig. 5. Comparison of simulation results and standard values.

The time and mean square error of each algorithm are shown in Table 7.

According to the comparison results in Table 7, the mean square error of the FAHP-CVF method based on the double-weighted method is smaller than that of other methods, and the results are closer to the standard values. To further verify the effectiveness and applicability of the proposed method, statistical analyses were conducted using the Pearson correlation coefficient, Spearman correlation coefficient, significance, and difference indicators based on the results obtained from four methods. The evaluation criteria are as follows:

1) Correlation Coefficient:

- If the correlation coefficient > 0.8 , it indicates a high level of consistency between the two methods.
- If $0.5 \leq \text{correlation coefficient} < 0.8$, it indicates a moderate level of consistency.
- If the correlation coefficient < 0.5 , it indicates significant differences between the two methods.

2) Significance:

- If significance < 0.05 , it indicates a significant correlation, and the results are statistically meaningful.
- If significance ≥ 0.05 , it suggests that the correlation might be random and requires further investigation.

3) Difference:

- If the difference < 0.05 , it indicates a significant difference between the two methods.
- If the difference ≥ 0.05 , it indicates no significant difference between the results of the two methods.

The analysis results are shown in Table 8.

Figure 7 shows the results and distribution differences of the two methods using scatter plots and box plots.

From Table 8; Fig. 7, it can be observed that the Pearson correlation coefficients and Spearman correlation coefficients between FAHP-CVF and BPNN, FAHP, and MDM methods are all greater than 0.8, indicating a high level of consistency between the proposed method and the other three methods. This demonstrates that the proposed method is consistently applicable to combat data quality evaluation, verifying the robustness of the results. The significance values between FAHP-CVF and BPNN, FAHP, and MDM methods are all less than

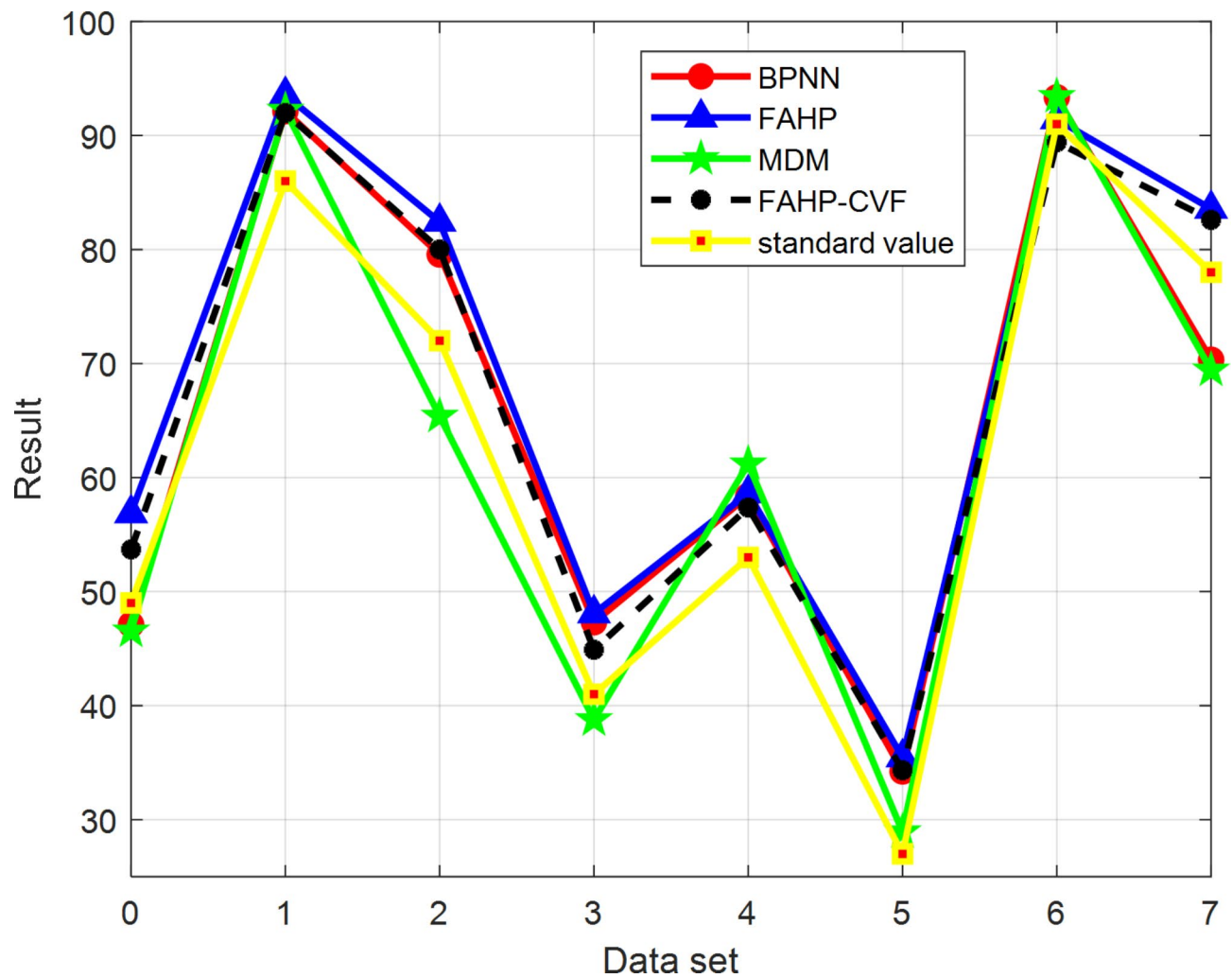


Fig. 6. Comparison of Algorithm Results.

	Standard Results	BPNN	FAHP	MDM	FAHP-CVF
M_1	49	47.12	56.87	46.54	53.7
M_2	86	92.14	93.55	92.22	91.98
M_3	72	79.57	82.43	65.38	80.01
M_4	41	47.32	48.08	38.76	44.9
M_5	53	58.4	58.62	61.2	57.37
M_6	27	34.23	35.45	28.93	34.33
M_7	91	93.35	91.42	93.42	89.42
M_8	78	70.34	83.57	69.43	82.6
Time		42.31s	6.35s	8.10s	7.62s
Mse		5.96	7.18	5.52	5.35

Table 7. Comparison results.

Comparison of methods	Pearson correlation coefficient	Spearman correlation coefficient	Significance	Difference
FAHP-CVF and BPNN	0.9707	0.9286	6.1774×10^{-5}	0.4578
FAHP-CVF and FAHP	0.9992	1.0000	1.2697×10^{-9}	4.2422×10^{-4}
FAHP-CVF and MDM	0.9533	0.9762	2.4633×10^{-4}	0.0968

Table 8. Statistical analysis table.

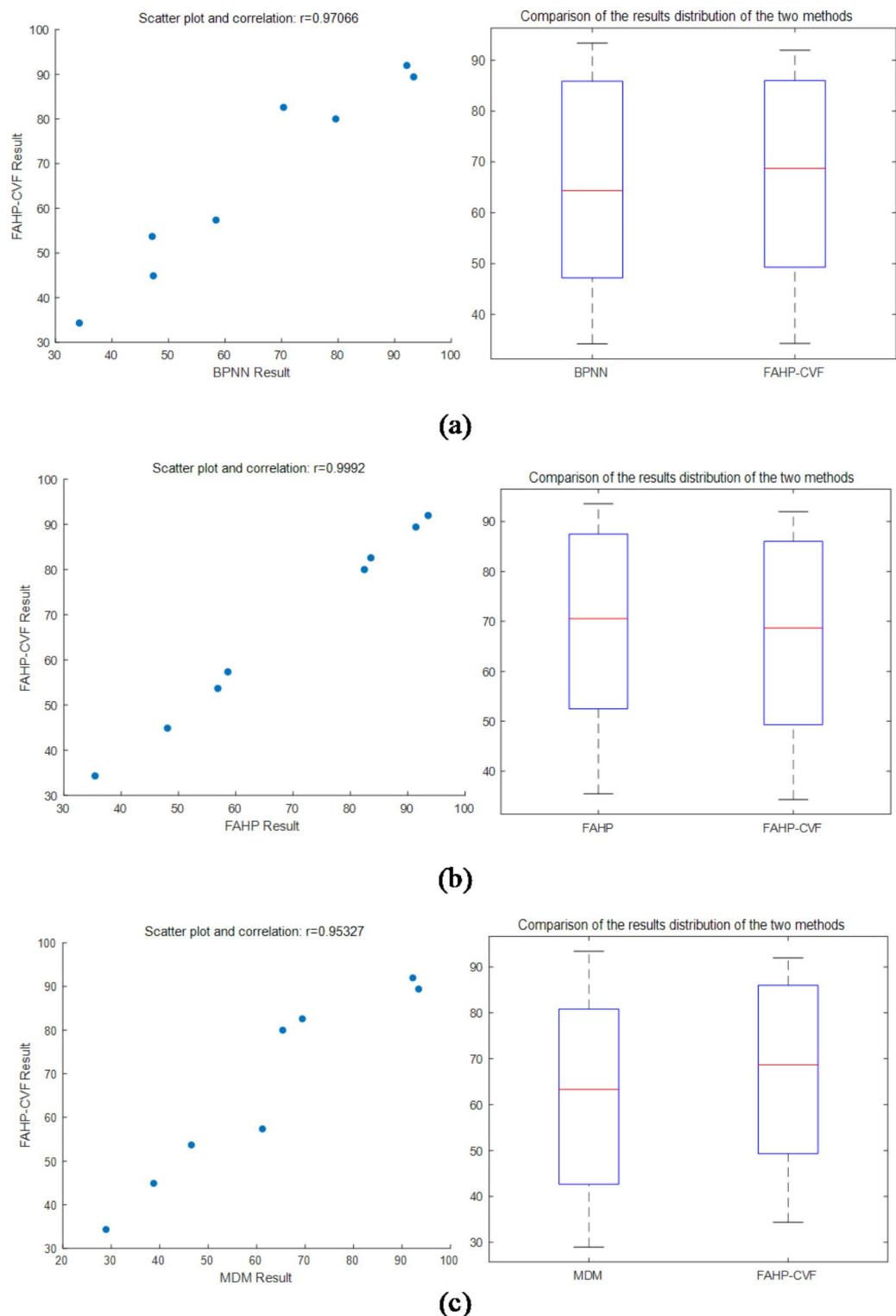


Fig. 7. Visual presentation.

0.05, indicating that the correlations are significant, and the result similarities are not caused by randomness, confirming their statistical validity. The difference values between FAHP-CVF and BPNN, as well as MDM methods, are greater than or equal to 0.05, indicating that the results of the proposed method are not significantly different from those of the other two methods, further supporting the robustness of the conclusions. Although there is a difference between FAHP-CVF and FAHP, the consistency in correlation coefficients and significance values suggests that the proposed method is an improvement over FAHP. It provides a more scientific and accurate evaluation of combat data quality, demonstrating its effectiveness and practical value.

Conclusion

Due to the inherent complexity of military operations and related issues, data quality problems become particularly prominent in large-scale military simulation and wargaming systems. As the input component of combat simulation systems, the quality of combat data directly impacts the accuracy and validity of the output results. To address the current challenges of inaccurate combat data evaluation, and in light of the limitations in domestic and international data quality evaluation methods, this study proposes a double-weighted based on FAHP optimized by CVF method for evaluating combat data quality. This method enhances the precision of existing combat data quality evaluation approaches. Experimental simulation results demonstrate that the proposed method is easy to understand and implement, with evaluation outcomes that are closer to the standard values. The method holds significant value in combat simulation and wargaming, as it can greatly improve the accuracy of such simulations and has substantial application potential in future military development. The focus of this research is on combat data quality in simulation and evaluation, with the innovation lying in the proposal of a reasonable assessment method for combat data quality. However, the study has certain limitations, such as a relatively small data scale and the influence of subjective factors. Although the limited research data restricts broad applicability, the proposed method itself is generalizable and applicable to any combat simulation evaluation. Future research should expand the dataset to consider a broader range of combat data and operational scenario factors, further optimizing the quality assessment methods and providing robust data support for the development of combat simulation evaluations.

Data availability

All data generated or analysed during this study are included in this published article [and its supplementary information files].

Received: 25 October 2024; Accepted: 17 January 2025

Published online: 20 January 2025

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ACKNOWLEDGEMENTS

This research was supported by the National Natural Science Foundation of China Key Project: Space-Earth Integration Intelligent Network Traffic Theory and Key Technology Fund Project (61931004).

Author contributions

Jianwei Wang mainly responsible for the simulation and writing of the paper, wrote the main manuscript text and prepared Figs. 1, 2, 3, 4, 5, 6 and 7. Chengsheng Pan mainly responsible for the research direction and writing guidance of the paper. Qing Zhang mainly responsible for the data collection and literature research of the paper. All authors reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1038/s41598-025-87266-3>.

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