Evaluation of the Effectiveness of the Security Protection System Based on the Improved AHP-FE Method

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Abstract. With the rapid development of information technology, security protection systems (SPS) have become vital for safeguarding data and resources. A significant decision-making challenge is presented to design an optimal security strategy amidst complex factors. This paper applies a combined approach of Fuzzy Evaluation (FE) and the Analytic Hierarchy Process (AHP) to enhance the design and evaluation of SPS. The methodology integrates FE for constructing an evaluation model to determine the appropriate weight of each index and AHP, paired with the Paired Majority Rule (PMR) and the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), to hierarchically analyze security factors. This approach creates a decision model based on consistency checks to derive the optimal security strategy. The results show that the proposed methods can effectively quantify complex security factors and generate optimized solutions for security protection. Experimental case studies validate the method's accuracy and reliability, demonstrating the wide application potential of integrating big data technology into complex decision-making processes for security systems.

Keywords: Fuzzy Evaluation (FE), Analytic Hierarchy Process (AHP), Security Protection System (SPS), Decision-making, Security Strategy.

1. Introduction

With the development of manufacturing industries, SPS are becoming increasingly significant. When production scales increase and technology advances, SPS will face safety risks during production. Effective SPS not only protects the lives of employees but also improves productivity and quality. Shaverdi et al. have shown that the application of SPS can significantly reduce the occurrence of production accidents [1]. In addition, Mohammed et al. proposes that SPS can promote the sustainable development of the manufacturing industries [2]. Therefore, the SPS is constructed and improved by Katarina in the common focus of researchers and users [3].

In recent years, researchers have proposed some methods to evaluate the effectiveness of SPS. The hierarchical analysis method (AHP) and the fuzzy comprehensive evaluation method (FCE) are widely used in the assessment and ability enhancement of SPS [4]. The effectiveness of SPS can be effectively enhanced by constructing an evaluation index and scientifically determining the weights of each index [5]. Petroustatou suggested that the construction of a holistic evaluation index is crucial for the procurement decision-making model [6]. Surhasono and Wei R proposed that some functions are derived from the AHP [7, 8] and others are derived from the voting methods (the paired majority rule (PMR)) to perform data aggregation methods and apply material element (ME) models to consider multiple factors [9], but as stated, the results of the models are sometimes limited to specific regions, thus the accuracy and real-time nature of the evaluation results are still needed to be improved [8]. Furthermore, Zhou J analyzed the application of multi-source material data fusion techniques through artificial intelligence algorithms and big data technologies [10], but this process is time-consuming and labor-intensive. Liu proposed that the methods can deal with complex and fuzzy information to indicate an inevitable correspondence between the way of interpreting and the way of normalizing the weights under each standard [11], but consistency is difficult to be fully guaranteed when dealing with lots of them.

To address the shortcomings of existing studies, researchers have made various improvements. An integrated method that combines the hierarchical analysis method (AHP) and the preference ranking organization method for enrichment evaluation (PROMETHEE) is proposed by Dağdeviren M [12], this method can increase the safety evaluation indexes and further refines and expands the existing index system, however, some of the standards have an uncertain structure leading to the problem can't be accurately measured. The evaluation results by improving data collection, and processing methods and applying big data technology can be improved, simultaneously, the accuracy and real-time nature of the evaluation results are also improved by Buduk [13], reflecting the actual trend of software evaluation in the era of big data, but this paper is mainly based on providing a new level of standards, and the speed and efficiency of computation may not be able to keep up with the speed of data updating, which leads to be delayed or untimely decision-making. In addition, Vinogradova-Zinkevič proposed that the fuzzy hierarchical analysis method (FAHP) is committed to establishing a reasonable and objective attribute weight evaluation index [14], however, there are not enough decision variables to draw generalized conclusions. Cui L Y adopted that hierarchical analysis-fuzzy comprehensive evaluation methods (FCE-AHP) [15], but it is difficult to reflect the change in SPS over time. Haktanır proposed that certain combination methods can be applied to complex decision-making processes, which is usually meaningful to subjective data or fuzzy information [16], and may help to solve more complex problems that may have more layers, but the paper could go further to incorporate different levels and detailed criteria consisting of social, political, environmental, and market requirements.

To solve the above problems, this study proposes an evaluation method based on the AHP-FE and the effectiveness of the SPS. By constructing a scientific evaluation index system, determining the weights of each index, and combining the FE, the effectiveness of the SPS is comprehensively and objectively evaluated. This study not only further improves the existing evaluation methods, but also introduces a dynamic evaluation model, which can reflect the changes of the SPS over time. In addition, the accuracy and reliability of the evaluation results are improved by improving the data collection and processing methods and applying big data technology and multi-source data fusion technology.

2. Feature extraction

2.1. Data preprocessing

Data preprocessing can effectively improve the accuracy of the model and avoid the negative impact of noise and abnormal values for the analysis results.

2.1.1 Normalization

Normalization is the process of scaling data to a specific range, and usually maps data to [0, 1] or [-1, 1] intervals. Common normalization methods include three aspects.

1) Min-Max Scaling: the data is linearly mapped to the [0, 1] interval, and the scaling is calculated by (1).

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Where X_{norm} is the normalized data, X is the original data, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the dataset. Usually, this interval is $[0,1]$. This interval can be various intervals, such as mapping to $[0,1]$ and continuing to map to other ranges.

2) The input data is converted to a range by using the following (2).

$$X^{'} = \frac{2\times(X - X_{\min})}{X_{\max} - X_{\min}} \tag{2}$$

Both of the above methods involve proportionally scaling the raw data. Among them, $X^{'}$ represents the normalized data, X is the original data size, $X_{\max}$ and $X_{\min}$ is the maximum and minimum values of the original data.

3) The method of normalizing to any intervals

The common data normalization is to normalize to the interval of $[0,1]$, or $[-1,1]$, but in some special cases, we need to normalize to any other interval according to the actual situation. The method of normalizing data to a range of $[a,b]$ intervals.

(1) Find the minimum Min and maximum Max values of the sample data Y

(2) The calculation coefficient is shown by (3)

$$k = \frac{(b-a)}{(Max - Min)} \tag{3}$$

(3) The normalized data is obtained to the interval $[a,b]$ by (4).

$$Y^{Nor} = a + k(Y - Min) \tag{4}$$

(4) Essentially, the general normalization function is expressed by (5).

$$y = \frac{(Y_{\max} - Y_{\min}) * (X - X_{\min})}{(X_{\max} - X_{\min}) + Y_{\min}} \tag{5}$$

2.1.2 Standardization

Standardization is different from normalization in that standardization does not have a fixed numerical interval, thus preserving the original distribution characteristics of the data. For many machine learning models, standardization can accelerate convergence speed and improve training efficiency. Standardization is the process of processing data based on the columns of the feature matrix. There are various methods for data standardization, such as straight-line methods (such as extreme value method and standard deviation method), zigzag methods (such as trilinear method), and curvilinear methods (such as semi normal distribution). Different standardization methods will have different impacts on the evaluation results of the system. Among them, the most commonly used is Z-Score standardization.

Z-score normalization, also known as standard deviation normalization or zero mean normalization, is the process of transforming data into a distribution with a mean of 0 and a standard deviation of 1, which retains the original data distribution after the transformation. The relationship can be expressed by (6).

$$X^{'} = \frac{X - \mu}{\delta} \tag{6}$$

Where μ is the mean of the original data, δ is the standard deviation of the original data, it is currently the most commonly used standardized formula. This method standardizes the data by taking the mean and standard deviation of the original data. The processed data conforms to a standard normal distribution, with a mean of 0 and a standard deviation of 1. The key here is the composite standard normal distribution.

2.2. Efficiency Evaluation Indicators of SPS

SPS efficiency evaluation indicators are used to measure the performance of SPS, helping users understand whether the system can effectively resist attacks and ensure network security. The performance evaluation indicators of SPS can be divided into three levels: first-class index, second-class index and third-level index.

2.2.1 First-class Index

The first-class index is the core dimension for evaluating the effectiveness of SPS, typically including the following aspects:

1) System reliability

The stability and reliability of a system are fundamental to evaluating the effectiveness of a security protection system. An efficient security system should be able to provide sustained and stable protection against various risks and threats. This indicator can be measured through data such as system failure rate and mean time between failures.

2) Response time

The response time of the security protection system is crucial when facing potential threats. The fast response can effectively reduce losses; therefore, response time is an important component of primary indicators, usually including two sub-indicators (detection time and disposal time).

3) Comprehensive protection

A comprehensive security protection system should have a certain degree of comprehensiveness and be able to respond to various types of risks and threats. The comprehensive protection capability can be evaluated through aspects such as system coverage and detection types.

2.2.2 Second-class Index

The second-class index supplies and divides the first-class index in more detail. The following is a breakdown of each first-class index:

1) System reliability

(1) Failure rate: The frequency of system failures occurring within a specific period of time.

(2) Mean Time to Repair (MTTR): The average time required to restore normal operation after a system failure.

(3) Service availability: The proportion of a system that is available at a specific time.

2) Response time

(1) Intrusion detection time: The time required for the system to detect intrusion behavior.

(2) Event response time: The time it takes to respond to a security incident.

(3) Recovery time: The time it takes for the system to resume normal operation after a security incident or failure.

3) Comprehensive protection:

(1) Risk coverage rate: The proportion of risk types that the system can identify and prevent.

(2) Warning capability: The system's ability to identify potential threats in advance and issue alerts.

(3) Diversity of protective measures: The diversity of protective tools and technologies adopted by the system.

2.2.3 Third-class Index

The Third-class Index is further refinement of the second-class index, usually involving specific measurement methods and parameters. These indices provide specific operational standards for implementing detailed performance evaluations.

1) Failure rate

(1) System software and hardware failures: The failure rate caused by both software and hardware failures.

(2) Human control error: The frequency of malfunctions caused by user operational errors.

2) Mean Time to Repair (MTTR)

(1) Repair response efficiency: whether the response is timely after the fault occurs.

(2) Technical support speed: The response speed and effectiveness of external technical support organizations.

3) Intrusion detection time

(1) Automatic detection time: The time required for the system to automatically identify intrusions.

(2) Manual intervention time: The time required to identify an intrusion when manual monitoring is required.

4) Risk coverage rate

(1) Number of preventive measures: The number of preventive measures taken for different types of risks.

(2) Successful defense cases: The number of successful defense cases against various attacks or intrusions.

Through the hierarchical construction of the first and third-level indicators, detailed parameter support can be provided for the comprehensive evaluation of the security protection system, ensuring the comprehensiveness and accuracy of the evaluation.

2.3. Solving method of the correlation matrix

2.3.1 FE method

The FE is a comprehensive evaluation method based on fuzzy mathematics theory. By constructing an evaluation system and membership function that matches the evaluation objectives, it achieves quantitative processing of factors with fuzzy boundaries and is difficult to directly quantify, and then comprehensively evaluates practical problems. It is suitable for dealing with situations where evaluation indicators have fuzziness and uncertainty. The basic idea is to use fuzzy set theory to quantify fuzziness and achieve a comprehensive evaluation of the evaluation object through fuzzy comprehensive evaluation.

1) Structure of Solving Method

Fuzzy comprehensive evaluation method is a comprehensive evaluation method based on fuzzy mathematics. This comprehensive evaluation method transforms qualitative evaluation into quantitative evaluation based on the membership theory of fuzzy mathematics, that is, using fuzzy mathematics to make an overall evaluation of things or objects that are constrained by multiple factors. The structure is shown in the Figure 1.

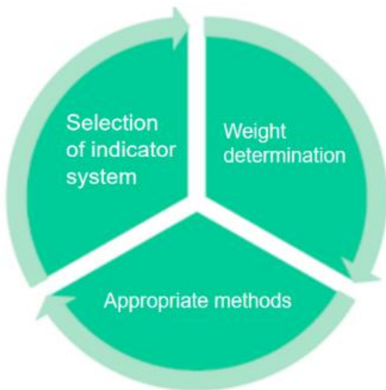

Figure 1. Structure of FE Method

(1) Determination of the evaluation index system: Based on the characteristics of the evaluation object, select appropriate evaluation indicators to form the evaluation index system.

(2) Establishment of evaluation level: Based on the actual situation, determine the FE levels of each evaluation indicator and provide the membership functions for each level. The indicator set of a fuzzy comprehensive evaluation is a collection of evaluation results formed by objectively evaluating the evaluation object. The evaluation set can be classified into multiple different levels based on specific circumstances $V = \{V_1, V_2, ..., V_i\}$. To characterize the i judgments in which each indicator is located.

(3) Construction of FE matrix: Through investigation or expert evaluation, a FE matrix is constructed to reflect the FE results of each evaluation object on various evaluation indicators. Using the membership formula to measure the evaluation level of each indicator, a single-factor evaluation membership matrix is formed by (7).

$$R_i = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{7}$$

(4) Evaluation of fuzzy comprehensive evaluation: Using fuzzy operations in fuzzy mathematics, the FE matrix is comprehensively evaluated to obtain the fuzzy comprehensive evaluation results of each evaluation object.

2) Solution Process of FE Method

(1) Membership Determination: Based on the membership function of the evaluation indicators and evaluation levels, calculate the membership degree of each evaluation object on each indicator.

Triangular fuzzy numbers are used for research. Triangular fuzzy numbers $\tilde{M}$ refer to fuzzy numbers in the domain R, and their membership functions $\mu_{\tilde{M}} : R \to [0,1]$ are expressed by (8).

$$\mu_{\tilde{M}}(x) = \begin{cases} \dfrac{x-l}{m-l}, x \in [l,m] \\ \dfrac{x-u}{m-u}, x \in [m,u] \\ 0, else \end{cases} \tag{8}$$

(2) Construct a fuzzy relationship matrix: Construct the membership degree results into a fuzzy relationship matrix, reflecting the fuzzy relationships of each evaluation object on each indicator. Construct a first-level fuzzy comprehensive evaluation: $B = \omega R$, where ω_i is the weight of the i layer, and then construct a second-level fuzzy comprehensive evaluation: $R = [B_1, B_2, ...B_i]^T$

(3) Fuzzy comprehensive operation: By using the weighted average method or fuzzy operator to perform the comprehensive operation on the fuzzy relationship matrix, the comprehensive evaluation result of the evaluation object is obtained. $P = AR$ is the evaluation result, where A is the weight of the indicator layer. There are four common fuzzy synthesis operators: $M(\wedge,\vee)$, $M(\bullet,\oplus)$, $M(\wedge,\oplus)$ and $M(\bullet,\oplus)$. Using different fuzzy synthesis operators will result in different FE conclusions.

For the operation of triangular fuzzy numbers, if $M_1 = (l_1, m_1, u_1)$ $M_2 = (l_2, m_2, u_2)$, the relationship is expressed by (9)-(10).

$$M_1 \oplus M_2 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{9}$$

$$M_1 \bullet M_2 = (l_1, m_1, u_1) \bullet (l_2, m_2, u_2) = (l_1 l_2, m_1 m_2, u_1 u_2) \tag{10}$$

The correlation matrix is used to represent the correlation between different indicators, which can help analyze the dependency relationship between the overall performance of the system and the degree of mutual influence between different indicators.

2.3.2 Correlation Matrix of First-class and Second-class

The first-class and second-class correlation matrices are used to describe the correlation between first-class and second-class indices. Table 1 shows the relevance of the first-class and second-class. For example, the correlation between system reliability and failure rate, mean time to repair (MTTR), and service availability can be analyzed. We can construct a correlation matrix of $n \times m$, where

a_{ij} represents the strength of the correlation between the $i-th$ primary indicator and the $j-th$ secondary indicator. Assuming the strength of the association is low (weak association), medium (moderate association), high (strong association), etc.

Table 1. Correlation between first-class and second-class index

First-class Index	Second-class Index	Relevance
system reliability	failure rate	high
	Average repair time (MTTR)	secondary
	Service availability	high
response time	Intrusion detection time	high
	Event response time	high
	recovery time	secondary
Comprehensive protection	Risk coverage ratio	high
	Warning capability	secondary
	Diversity of protective measures	high

Establishing a scientific evaluation index system is an important way to enhance the effectiveness of SPS. The First-class index, second-class index, and their correlation matrices provide a Intuitive framework, making the evaluation process more systematic and efficient. By continuously optimizing and monitoring these indicators, it is possible to ensure that the security protection system maintains high efficiency in the face of complex and changing environments and threats, thereby providing security and stability for society.

2.3.3 Secondary and corresponding tertiary correlation matrices

The second-class and third-class correlation matrices are used to describe the correlation between second-class and third-class indices. Table 2 shows the relevance of the second-class and third-class.

Table 2. Correlation between second-class and third-class index

Second-class Index	Third-class Index	Relevance
Failure rate	System software and hardware malfunction	high
	Human control error	secondary
Average repair time (MTTR)	Repair response efficiency	high
	Technical support speed	secondary
Intrusion detection time	Automatic detection time	high
	Manual intervention time	secondary
Event response time	Event classification and priority setting	high
	Related event processing time	secondary
recovery time	Effectiveness of recovery strategy	high
	Data recovery time	secondary
Risk coverage ratio	Number of preventive measures	high
	Successful defense case	secondary
Warning capability	Warning threshold setting	high
	Efficiency of early warning information transmission	secondary
Diversity of protective measures	Types of Protective Technologies	high
	Multi-layer protection strategy integration	secondary

From this correlation matrix, we can see the complex relationship between the second-class and third-class index. For example, the failure rate has a strong impact on system software and hardware failures, while its impact on human control errors is relatively weak. Through such a matrix, evaluators can more clearly identify the key factors that affect the evaluation results, and thus prescribe targeted measures to enhance the effectiveness of the safety protection system. This matrix can help security managers better understand the correlation between various indicators and take effective measures for optimization.

3. The improved AHP-FE Algorithm

3.1. AHP algorithm

The AHP is a structured technique for analyzing and resolving complex problems by decomposing them into relevant factors. These factors are organized into a hierarchical model based on their relationships. The relative importance of each factor is determined through expert judgment or experiential knowledge, allowing for a quantitative analysis and comparison of these factors. AHP is designed to quantify the relative priorities of a set of alternatives on a ratio scale, relying on the decision maker's judgments. The method emphasizes the importance of intuitive judgment and ensures consistency in comparing alternatives throughout the decision-making process.

3.1.1 Structure of AHP

The AHP systematically decomposes a decision-making event into three hierarchical levels: the goal level, the criterion level, and the solution level. The goal level represents the overarching objective of the decision-making process. The criterion level consists of the various criteria or standards that influence the attainment of this goal. Finally, the solution level encompasses the potential alternatives or options available for achieving the objective.

3.1.2 Solution process

1) Hierarchical structure model:

According to the decision-making problem, establish a multi-level structure model containing the target layer, criterion layer and program layer.

2) Judgment matrix:

Through the method of pairwise comparison, experts are invited to judge the relative importance of each factor in each layer, and the judgment matrix is constructed as shown in (11).

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

Where a_{ij} means the degree of importance of indicator i compared to indicator j. When i=j, i.e., the meaning of the two indicators is the same, this is noted as 1, corresponding to the elements of the main diagonal are equal to 1. Where a_{ij} and a_{ij} are reciprocals of each other and satisfy $a_{ij} . a_{ij}$ =1.

In conventional decision-making, the relationships between multiple indicators are often inadequately considered, making pairwise comparisons essential. AHP uses a nine-point scale (1-9) for these comparisons, where 1 represents equal importance, 3 slight importance, 5 clear importance, 7 strong importance, and 9 extreme importance. Although this scale is simple and easy to use, it fails to address the inherent uncertainty in converting subjective judgments into numerical values.

Table 3. Relevance Scale

Scale	Hidden Meaning
1	The two factors are of equal importance compared to each other
3	One factor is slightly more important than the other when comparing the two factors
5	One factor is significantly more important than the other when comparing two factors
7	One factor is more strongly important than the other when compared to the two factors
9	The extreme importance of one factor over the other when comparing two factors
2, 4, 6, 8	The median of the above two neighboring judgments

3) Consistency assessment:

Consistency analysis of the judgment matrix ensures that the judgments remain consistent. If inconsistency is detected, the judgment matrix must be adjusted, followed by recalculating the relevant values.

The judgment matrix needs to be normalized to calculate the consistency metric *CI*.

$$CI = \frac{\lambda_{max}}{n-1} \tag{12}$$

The next step involves determining the average random consistency metric RI.

Table 4. Corresponding values of RI

n	1	2	3	4	5	6	7
RI	0	0	0.52	0.89	1.12	1.26	1.36

When the number of n is too large it is necessary to consider the expansion of the indicator system, and finally it is necessary to calculate the consistency ratio CR.

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

If CR < 0.1, the consistency of the judgment matrix can be considered acceptable, otherwise the judgment matrix needs to be corrected.

4) Comprehensive weight calculation:

The weight vectors of each level are combined and calculated to get the final weight of each program.

According to Eq. (11), for the calculation of the weight vector, there are three methods for solving here, which are arithmetic mean, geometric mean and eigenvalue method, and these three methods are used to solve the weights in the following.

Weights by arithmetic averaging is expressed by (14).

$$\omega_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \tag{14}$$

Weights by geometric averaging is expressed by (15).

$$\omega_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{k=1}^{n}\left(\prod_{j=1}^{n} a_{kj}\right)^{\frac{1}{n}}} \tag{15}$$

For the eigenvalue method, the consistency matrix has one eigenvalue of n,and the rest of the eigenvalues are 0. When the eigenvalue is n, the corresponding eigenvector is: $k[\frac{1}{a_{11}},\frac{1}{a_{12}},\ldots,\frac{1}{a_{1n}}]^T$, and this eigenvector corresponds exactly to the first column of the consistency matrix.

The maximum eigenvalue can be solved by (16).

$$\lambda = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{W_{imax}} \tag{16}$$

If the consistency of our judgment matrix is acceptable, then we can follow the method of finding the weights of the consistent matrix by first finding the largest eigenvalue of the matrix A and its corresponding eigenvector, and then normalizing the eigenvectors to get our weights.

3.2. Improved AHP-FE Algorithm

In the traditional comprehensive fuzzy judgment method, weight coefficients are typically assigned as constants based on experience. However, this approach has a significant limitation as it fails to account for varying practical situations. The core of AHP involves using integers between 1 and 9, along with their reciprocals, to construct the judgment matrix, with the evaluator's estimation being determined as a precise number. This often overlooks the inherent ambiguity in human judgment. When the weight ratio between two factors, i and j, is difficult to determine and is only known to vary between p and q, with m being the maximum possible value, this scenario represents fuzzy judgment. To better capture such uncertainty, it is essential to extend AHP within a fuzzy environment, thereby enhancing its ability to handle the imprecision and vagueness in decision-making processes.

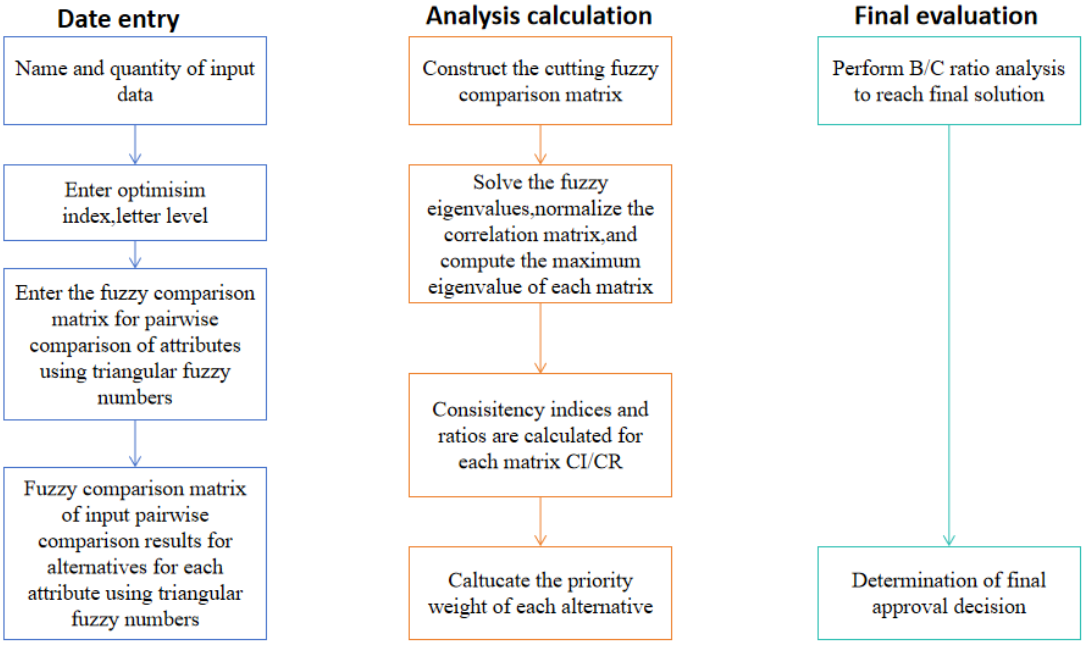

Figure 2. Flow chart of AHP-FE method

The specific improvements are as follows:

1) Determine the weight coefficients using the AHP method:

Construct a multilevel structural model through hierarchical analysis, establish a judgment matrix, and perform a consistency assessment to calculate the weight coefficients of each factor.

For the hierarchical structure determined by AHP, further matching comparison assessment with fuzzy degree is required, using five linguistic terms "very unimportant" (VU), "less important" (LI), "equally important" (EI), "more important" (MI) and "very important" (VI) ranging from 0-9 to construct a fuzzy comparison matrix. The fuzzy comparison matrix was constructed using five linguistic terms "very unimportant" (VU), "less important" (LI), "equally important" (EI), "more important" (MI), and "very important" (VI) ranging from 0-9. For these five classifications, the affiliation function can be expressed by (17)-(21).

$$X(\alpha)_{VU}=\begin{cases} X_{\alpha,L}=0 \\ X_{\alpha,M}=\frac{0.5+(X_{\alpha,L}-1)[(X_{\alpha,L}-1)(0.33+0.17\alpha)+1]}{1+(0.5X_{\alpha,L}-0.5)(1+\alpha)} \\ X_{\alpha,R}=2-\alpha \end{cases} \tag{17}$$

$$X(\alpha)_{LI}=\begin{cases} X_{\alpha,L}=1+1.5\alpha \\ X_{\alpha,M}=2.5 \\ X_{\alpha,R}=4-1.5\alpha \end{cases} \tag{18}$$

$$X(\alpha)_{EI}=\begin{cases} X_{\alpha,L}=3+2\alpha \\ X_{\alpha,M}=5 \\ X_{\alpha,R}=7-2\alpha \end{cases} \tag{19}$$

$$X(\alpha)_{MI}=\begin{cases} X_{\alpha,L}=6+1.5\alpha \\ X_{\alpha,M}=7.5 \\ X_{\alpha,R}=9-1.5\alpha \end{cases} \tag{20}$$

$$X(\alpha)_{VI} = \begin{cases} X_{\alpha,L} = 8 + \alpha \\ X_{\alpha,M} = 8 + \frac{1.5+(9-X_{\alpha,L})[(9-X_{\alpha,L})(0.67+0.17\alpha)+0.5]}{1+(4.5-0.5X_{\alpha,L})(1+\alpha)} \\ X_{\alpha,R} = 9 \end{cases} \tag{21}$$

For the calculation of fuzzy weights, the following formula can be applied.

$$\widetilde{W} = (\tilde{a}, \tilde{b}, \tilde{c}) = \left[\frac{(\sum_{i=1}^{n} a_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} c_{ij})^{\frac{1}{n}}}, \frac{(\sum_{i=1}^{n} b_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} b_{ij})^{\frac{1}{n}}}, \frac{(\sum_{i=1}^{n} c_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}} \right] \tag{22}$$

The fuzzy weights are then defuzzified fuzzy weights, this step uses the method for defuzzification.

$$V = \frac{[(\tilde{c}-\tilde{a})+(\tilde{b}-\tilde{a})]}{3} + \tilde{a} \tag{23}$$

2) Constructing FE matrix:

The weight coefficients calculated by the AHP method are used to construct the FE matrix, which reflects the fuzzy judgment results of each evaluation object on each evaluation index. The clear weight of each element can be obtained by normalizing the number of defuzzified weights, which can be used in the following (24).

$$W = \begin{bmatrix} V_1 / \sum_{i=1}^{n} V_i \\ V_2 / \sum_{i=1}^{n} V_i \\ \vdots \\ V_n / \sum_{i=1}^{n} V_i \end{bmatrix} \tag{24}$$

3) Fuzzy comprehensive judgment:

By applying fuzzy operations within the framework of fuzzy mathematics, an FE matrix can be constructed. This matrix is then subjected to a comprehensive judgment process, ultimately yielding the fuzzy comprehensive evaluation results for each evaluation object.

This paper introduces an improved AHP-FE algorithm that enhances weight allocation and refines the fuzzy comprehensive judgment process. The study demonstrates that the proposed algorithm offers greater accuracy and reliability in addressing complex decision-making problems, effectively managing the vagueness and uncertainty inherent in evaluation indexes. Future research could explore the algorithm's application across various domains, potentially integrating big data technology to further enhance its intelligence and automation capabilities.

4. Arithmetic simulation

4.1. Setup of simulation

MATLAB (2022a) is employed to simulate the safety performance evaluation of the machinery. In modern industrial production, evaluating the safety of mechanical equipment is crucial for ensuring both smooth operations and personnel safety. To conduct a scientifically sound and rational assessment, a comprehensive evaluation method involving multiple indicators is typically used. In this simulation, 10 key mechanical evaluation indicators are selected, including noise level, efficiency, energy consumption, maintenance cost, vibration amplitude, operational stability, material strength, wear rate, temperature control accuracy, and equipment service life. These indicators encompass various aspects of mechanical performance, both positive and negative. By standardizing these indicators and determining their weights through fuzzy hierarchical analysis, we can more accurately assess the overall safety of different mechanical systems, providing a robust scientific foundation for equipment selection and management.

The objective of this simulation is to ultimately derive a safety score for the machinery through standardized processing, calculation of the correlation coefficient matrix, and iterative solution of the AHP-FE. The results are then visualized to assist decision-makers in making informed judgments. In this context, four sets of machine data corresponding to the 10 selected indicators are evaluated using the FE method, which enhances the precision of the AHP weight selection. The precision of the FE was set to 0.001. The four data sets are subsequently scored and ranked using the AHP-FE method, allowing for a comparative analysis of their safety performance.

4.2. Results of Cases

The *CI* is calculated to be 0.0411, and the *CR* is 0.03571. Since the *CR* value is less than 0.1, it indicates that the matrix passes the consistency test and its consistency is deemed acceptable. By solving the problem, the safety indices for the four groups of machines are determined as 0.37179, 0.52187, 0.51427, and 0.49193, respectively. The histograms of these four data sets are displayed in Figure 3 below, providing a visual representation of the results.

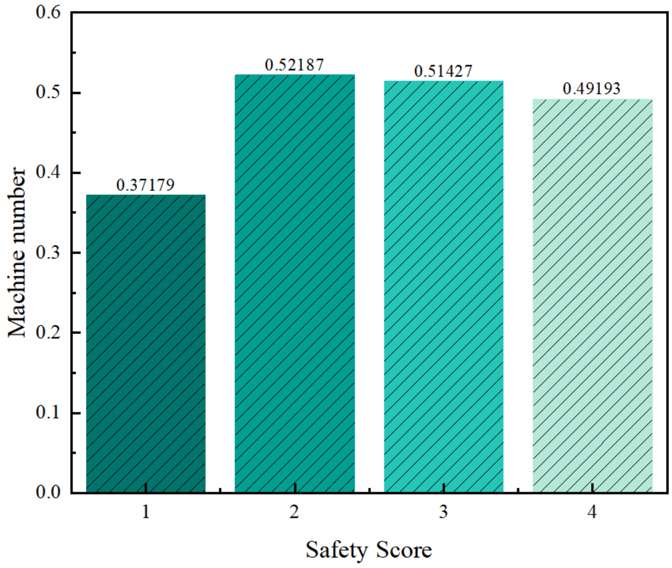

Figure 3. Mechanical Safety Scoring Chart

The chart allows the proposed method to rank the safety of these four types of machinery. From highest to lowest safety, the ranking is as follows: Machinery 2, Machinery 3, Machinery 4, and Machinery 1. This ranking provides a valuable reference for future machinery utilization.

The weights corresponding to each of the 10 indicators are presented in Figure 4 below.

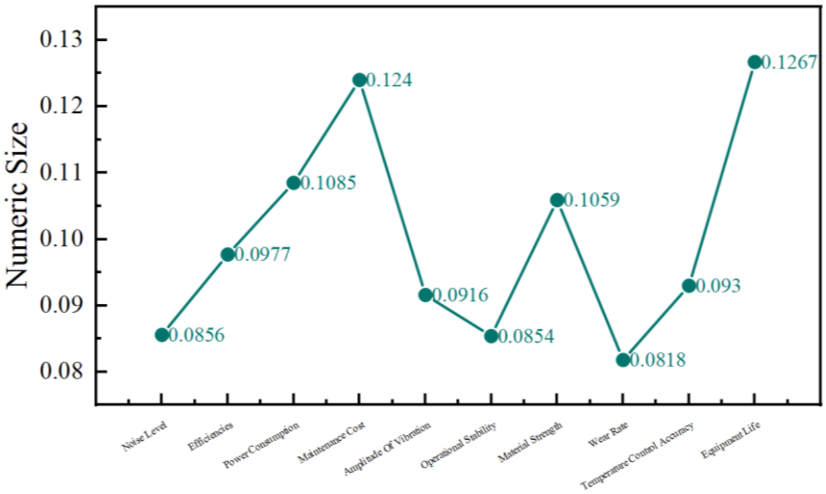

Figure 4. Distribution of weight values

It can be observed from the images here that among the 10 indicators selected, the weights of the two indicators, maintenance cost, and equipment life, are clearly higher than the others, so when considering the safety performance of the machinery in use, it is important to focus on these two indicators to meet the requirements. At the same time, the noise level, operational stability, and wear rate of the three indicators of the weight are significantly lower than the weight of the other indicators, in consideration of the assessment of the safety performance of the machinery, you can reduce the examination of these three indicators, with more energy to test the other indicators of the situation, which can make the highest efficiency, meanwhile, the waste of energy becomes less.

FE-AHP combines the strengths of the traditional AHP and fuzzy mathematics, making it particularly advantageous for complex decision-making problems. FE-AHP effectively handles uncertainties and ambiguities inherent in expert judgments, addressing limitations of traditional AHP, which often struggles with subjective and imprecise information. FE-AHP can improve decision accuracy by up to 20-30% compared to conventional AHP methods. By incorporating fuzzy numbers, FE-AHP allows for a more precise expression of expert opinions, enhancing the robustness and reliability of the model. Additionally, FE-AHP offers high flexibility and adaptability, making it a powerful tool for multi-criteria decision analysis, especially in scenarios involving complex, multi-level, and multi-objective problems.

5. Conclusion

This study systematically analyzed various factors in security systems using FE and the Analytic Hierarchy Process (AHP), showing that improved FE-AHP can effectively address complex decision-making problems. The results indicate that FE-AHP not only quantifies the different factors in SPS but also provides an optimized combination of security strategies based on the importance of each factor. While the application of big data technologies supports the approach, further validation in diverse real-world contexts is necessary to fully establish its reliability and adaptability.

In the future, research should focus on integrating artificial intelligence (AI) with the FE-AHP method to enhance decision-making and explore its applications in other industries for more dynamic and automated solutions.

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