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A Comprehensive Safety Risk Evaluation Method for Low-Altitude Flights

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Abstract

To scientifically identify and assess the safety risks of low-altitude flights, this study adopted the "human-machine-environment-management" framework from safety systems engineering theory. A total of 23 risk factors affecting safe operations were initially identified and extracted, forming a safety evaluation index system for low-altitude flight projects. Subsequently, the Likelihood-Exposure-Consequence (LEC) risk evaluation model was applied to these 23 risk factors using a "qualitative-quantitative-qualitative" approach to extract 10 key risks for low-altitude flights. The weight values of these key risk indicators were calculated using a game-theory-based combination weighting method. Finally, a safety risk evaluation method integrating the LEC model, game theory, and a backpropagation neural network was developed using deep learning algorithms. Using the Fuxi Mountain paragliding project in Zhengzhou, China, as a case study, the safety risk level of the low-altitude flight project was assessed, and the feasibility of the evaluation model was validated. Results show that the maximum safety risk level for the project is 63.632, while the minimum is 58.543, categorizing it as relatively unsafe. Key influencing factors include pilot psychological quality, safety and protective equipment, enterprise supervision, and low-altitude training exercises. The findings provide a method support for safety management and emergency decision-making in low-altitude flight projects.

Keywords: Low-altitude flight; BP neural networks; Flight safety; Risk evaluation

1. Introduction

With the opening of global low-altitude airspace and the development of national economies, the demand for low-altitude flight activities has surged. The 2024 Chinese government work report proposed fostering new growth engines, such as the low-altitude economy, signaling a golden development opportunity for low-altitude flight operations [1]. Data show that in the first half of 2023 alone, low-altitude passenger flight operations in China reached approximately 15,000 hours with around 300,000 passengers [2]. However, low-altitude flights inherently involve high-risk activities; once accidents occur, they are difficult to control and can lead to significant casualties and property losses. In recent years, a number of safety risk incidents caused by low-altitude flights have occurred worldwide. For example, in May 2018, a roller coaster stopped mid-air at Universal Studios Osaka, Japan, leaving 32 passengers stranded approximately 40 meters above the ground. On January 3, 2022, a high-altitude fall accident at the Moganshan Jinding Paragliding Base in Zhejiang, China, resulted in one fatality. The risks associated with low-altitude flights are numerous and involve complex coupling mechanisms, among various factors [3], making safety risk management exceptionally challenging. Therefore, identifying key safety risk indicators for low-altitude flight operations and proposing scientific safety evaluation measures are fundamental to effectively mitigating flight accidents.

Existing studies on safety risks in low-altitude flight operations predominantly focus on human factors, such as pilots, management personnel, and air traffic controllers [4–6]. Meanwhile, factors related to equipment maintenance and upgrades, power systems, communication and navigation, as well as environmental factors such as weather conditions, terrain, and flight obstacles, receive insufficient attention. There is a lack of systematic exploration and analysis of safety risks from a micro-level perspective across multiple dimensions, including personnel, equipment, environment, and management. Furthermore, risk evaluation methodologies for low-altitude flights often rely on specific indexes for partial risks, potentially leading to an incomplete and subjective analysis of overall risk levels. These methods are also inadequate in identifying the importance of key risk factors and assessing their consequences on accidents. To address these gaps, the present study selects safety risk indicators for low-altitude flights from four dimensions: personnel, equipment, environment, and management. It analyzes the influence intensity of different factors, identifies key evaluation indicators, and extracts critical risk indicators for safety assessment. Leveraging deep learning techniques, the study proposes a safety risk evaluation method for low-altitude flights and formulates targeted safety risk management strategies to provide decision-making support for their safe operation.

2. State of the Art

In terms of study methods, current studies on system safety evaluation models predominantly utilize mathematical approaches, such as analytic hierarchy process (AHP), fuzzy comprehensive evaluation, and gray relational analysis [7–8]. For example, Wang et al. [7] evaluated factors influencing

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aviation security based on fuzzy comprehensive evaluation. Dong et al. [8] proposed a safety risk evaluation model for lead-zinc mines using a fuzzy-gray relational analysis approach. Gyles et al. [9] developed an air traffic control safety evaluation system based on an ATC cooperative framework. Tong et al. [10] applied variable fuzzy set theory to evaluate the safety of rock engineering systems. Zhao et al. [11] integrated fuzzy theory and gray system theory to propose a risk evaluation model for helicopter sightseeing projects, reducing uncertainty through quantitative analysis. Furthermore, Swaim [12] employed a Bayesian network model to predict risk probabilities in hot air balloon projects, demonstrating strong adaptability and accuracy in addressing uncertainties in weather and mechanical failures. Arshad et al. [13] introduced a machine learning-based risk prediction model that utilizes flight data for pattern recognition and prediction, enhancing the intelligence level of risk assessments. In summary, these evaluation methods are computationally straightforward and have shown effective results. However, their practical applications reveal limitations, such as significant subjectivity in determining hazard scores or weights and a lack of self-learning and adaptive capabilities, which can affect the scientific validity and accuracy of the evaluations to some extent. Regarding study content, scholars both domestically and internationally have primarily focused on three aspects of low-altitude flight safety risk analysis: low-altitude airspace capacity, low-altitude route planning, and low-altitude risk factor analysis. The study paradigm generally follows a process from theoretical analysis and model construction to simulation experiments [14–16], aiming to comprehensively assess the safety risks of low-altitude flights to ensure their safety and efficiency. During the evaluation of low-altitude flight safety risks, study perspectives predominantly revolved around three dimensions: safety assurance technology, trajectory conflict prediction, and safety path planning. For instance, Mott et al. [17] proposed a two-step radar/vision sensor fusion method to evaluate the detection and tracking performance of low-altitude aircraft. Zhu et al. [18] introduced a multi-strategy particle swarm algorithm based on exponential noise to solve penetration issues in low-altitude safety spaces. However, existing studies primarily addressed low-altitude airspace safety issues, including route planning, conflict prediction, and capacity analysis. A deeper exploration of the risk factors affecting low-altitude flight safety, evaluations of aircraft safety levels, and strategies for safety management is needed.

On this basis, this study employs text mining methods to extract safety risk factors for low-altitude flights and establish a comprehensive safety risk evaluation index system. Through surveys conducted with government departments, operating enterprises, and domain experts, the LEC risk evaluation method is applied to identify critical risk factors for low-altitude flights. Subsequently, the weights of the evaluation indexes are calculated using a game-theory-based combination weighting method. The safety levels of low-altitude flights are dynamically assessed by integrating these results with a backpropagation (BP) neural network algorithm, and an evaluation method is designed. Finally, the proposed method is applied to a specific case to verify its scientific validity and feasibility, aiming to provide support and reference for the safety evaluations of low-altitude flights.

The remainder of this study is organized as follows: Section 3 elaborates on the identification methods for low-altitude flight risk factors, including the correlation-based and difficulty-based weighting of indexes, and provides a comprehensive explanation of the game-theory-based combination weighting method. It also details the internal computational processes of the input, hidden, and output layers in the BP neural network. Section 4 presents the result analysis. Finally, Section 5 summarizes this study and provides relevant conclusions. The framework and approach adopted in this study are illustrated in Fig. 1.

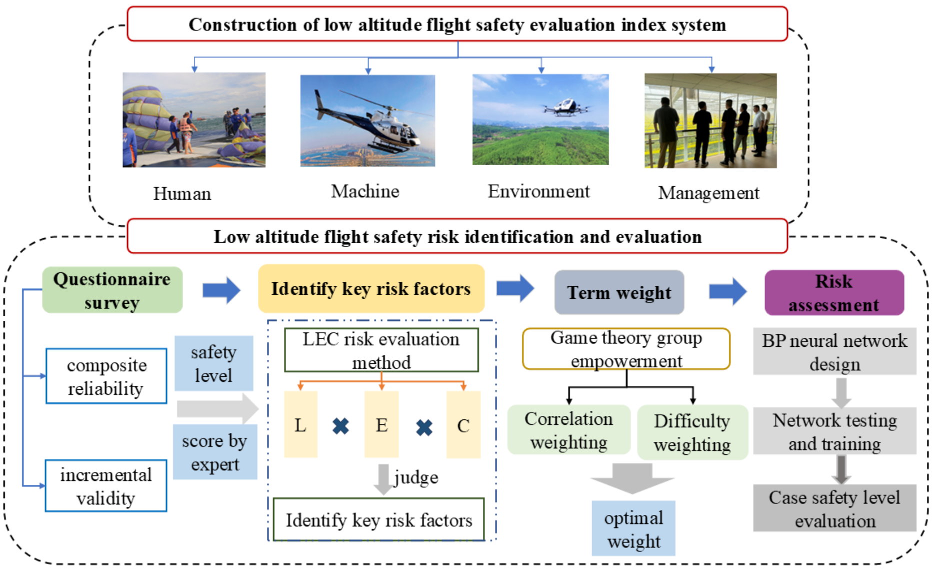

Fig.1. Research ideas and framework

3. Methodology

3.1 LEC risk evaluation method

In this study, the possibility of low-altitude flight safety risks, the frequency of exposure to dangerous environments, and the consequences of accidents were qualitatively analyzed via LEC risk evaluation method [19]. The risk value D of this method is expressed by the product of the index values of three main factors: L, E and C (i.e., $D = L \times E \times C$). L denotes the occurrence probability of an accident, E is the frequency of exposure to dangerous environments, C is the consequence of the accident, and D is the low-altitude flight risk value. The key after determining the D value lies in how to determine the threshold value of the risk level. This boundary value is fixed for a long time and can be determined in different periods according to the specific conditions. In this study, the risk boundary value was set to 120 based on Ref. [19].

3.2 Determination of index weights based on combination weighting of game theory

To determine the index weights for low-altitude flight safety evaluation indexes, this study put forward a calculation method based on combination weighting of game theory. The proposed method ensures the accuracy and comprehensiveness of weight calculation, reduces the subjectivity of weight determination, and provides support for determining the weights of evaluation indexes for low-altitude flight safety.

3.2.1 Correlation weighting of evaluation indexes

Index correlation weighting is an objective weighting method based on index differences and correlations. The weight is calculated on the basis of contrast intensity and conflict [20] as presented below.

1) Standardization of evaluation indexes. n low-altitude flight programs and m evaluation indexes are set. x_{ij} is the original data of the j-th evaluation index of the i-th program, and y_{ij} is the standardized data of the j-th evaluation index of the i-th program. When the higher value of an index indicates greater importance, standardization is performed via Equation (1):

$$y_{ij}=\frac{x_{ij}-\min_i(x_{ij})}{\max_i(x_{ij})-\min_i(x_{ij})} \tag{1}$$

When a lower index value means greater importance, standardization is implemented using Equation (2):

$$y_{ij}=\frac{\max_i(x_{ij})-x_{ij}}{\max_i(x_{ij})-\min_i(x_{ij})} \tag{2}$$

where $\bar{x}_{\bullet j}$ is the mean value of the j-th evaluation index:

$$\bar{x}_{\bullet j}=\frac{1}{n}\sum_{i=1}^{n}x_{ij} \tag{3}$$

2) Information amount of evaluation indexes. The correlation coefficient between the j-th evaluation index and the j`-th evaluation index is $r_{ij'}$, $r_{ij'}$ which is a statistical index reflecting the correlation between indexes.

$$r_{ij'}=\frac{\frac{1}{n-1}\sum_{i=1}^{n}(y_{ij}-\bar{y}_{\bullet j'})(y_{ij}-\bar{y}_{\bullet j'})}{\sigma_j\sigma_{j'}} \tag{4}$$

where σ_j is the standard deviation of the j-th evaluation index, and $\sigma_{j'}$ is the standard deviation of the j`-th evaluation index. Then, the total conflict $f_j=\sum_{j'}^{m}(1-r_{ij'})$ between the j-th evaluation index and all other indexes is calculated, with f_j representing the negative correlation between two indexes. Furthermore, the information amount contained in the j-th evaluation index is acquired:

$$c_j=\sigma_j f_j \tag{5}$$

3) Objective weights of evaluation indexes. The objective weight w_j^k of the j-th evaluation index is solved as follows:

$$w_j^k=\frac{c_j}{\sum_{j=1}^{m}c_j} \tag{6}$$

where m is the number of all indexes.

3.2.2 Difficulty weighting of evaluation indexes

1) The standard deviation of the j-th index is calculated using standardized data, and σ_j is used for index standardization [20].

$$\sigma_j=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_{ij}-\bar{y}_{\bullet j})^2} \tag{7}$$

2) Degree of deviation of the maximum value of an evaluation index from its mean value.

$$z_j=\frac{\max(y_{ij})-\bar{y}_{\bullet j}}{\sigma_j} \tag{8}$$

where y_{ij} is the index value (i.e., the value of the j-th index of the i-th program), and σ_j denotes the standard error.

3) Objective weights of evaluation indexes. z_j is standardized to obtain the difficulty weight ω_j^k of each index:

$$w_j^k=\frac{z_j}{\sum_{j=1}^{m}z_j} \tag{9}$$

3.2.3 Combination weighting of game theory

In index weighting, the correlations and differences between indexes are weighted, and difficulty weighting can be realized according to the difficulty in increasing the index. To balance the different influences of the two methods on index weights, they are combined by introducing combination weighting of game theory [20]. With the optimization objective of minimizing the weight deviation, the optimal combination weight can be adopted to reduce the limitations of the single weighting method, with the specific calculation steps as follows:

1) Weights are respectively assigned to indexes using the L-th method, and the L-th weight of the index is acquired:

$$w(k)=[w_{k1},w_{k2},\cdots,w_{kn}],k=1,2,\cdots,L. \tag{10}$$

Any linear combination of weights is as follows, where α_k is the linear combination coefficient and $\alpha_k > 0$.

$$w=\sum_{k=1}^{L}\alpha_k w_k^T. \tag{11}$$

2) The optimal combination coefficient is determined by following the combination weighting idea of game theory. By minimizing the deviation of w from each w_k, the L weight combination coefficients in Equation (11) are optimally processed to obtain the most ideal weight value in w, and the objective function is set as follows:

$$\min\left\|\sum_{k=1}^{L}\alpha_k w_k^T - w_k\right\|,\quad k=1,2,\cdots,L. \tag{12}$$

According to the matrix differential property, the linear equations for the optimal first-order derivative conditions of Equation (13) are as follows:

$$\begin{bmatrix} w_1\cdot w_1^T & \cdots & w_1\cdot w_L^T \\ \vdots & \ddots & \vdots \\ w_L\cdot w_1^T & \cdots & w_L\cdot w_L^T \end{bmatrix}\begin{bmatrix}\alpha_1\\ \vdots \\ \alpha_2\end{bmatrix}=\begin{bmatrix} w_1\cdot w_1^T \\ \vdots \\ w_L\cdot w_L^T\end{bmatrix}. \tag{13}$$

3) Calculation of combination weight. After α_k is normalized, the combination weight $w*$ of evaluation indexes for the undergraduate program is determined per Equation (14):

$$w*=\sum_{k=1}^{L}\alpha_k w_k^T,\quad k=1,2,\cdots,L. \tag{14}$$

3.3 BP neural network algorithm

In 1985, Rumelhart and McClelland et al. proposed the error BP learning algorithm of BP networks, which is a neural network capable of self-organization toward the direction that meets the given input-output relationship [21]. The BP neural network structure is shown in Fig. 2. The evolution process of things is analyzed through input and output layer nodes. The algorithm is mainly divided into two stages. In Stage 1 (forward propagation), the input information is processed layer by layer from the input layer through the hidden layer, and the actual output value of each unit is calculated. In Stage 2 (BP), if the output layer fails to get the expected output value, then the difference (i.e., the error) between the actual and expected outputs is recursively calculated layer by layer to correct the weight of the previous layer according to this difference [21].

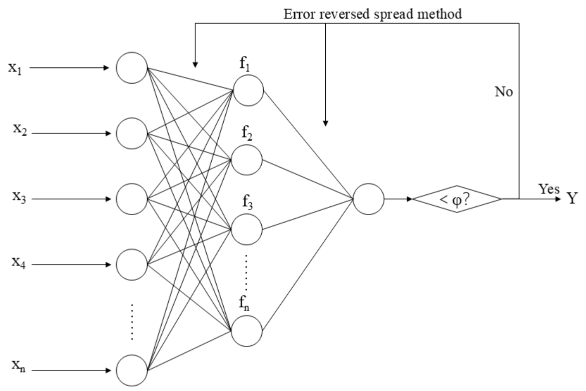

Fig.2. Structural chart of the BP neural network

The BP neural network is a training algorithm of an acyclic multilevel network, and its learning process consists of forward propagation and BP. The input value is processed layer by layer from the input layer through hidden units after nonlinear transformation and transmitted to the output layer. The state of neurons in each layer affects the state of neurons in the next layer. If the expected output cannot be obtained at the output layer, then BP will be initiated, and the error signal will be minimized by modifying the weights of neurons. The usual BP training algorithm can be described as follows [21]:

1) Input of BP neural network: $X(p) = \{x_1(p), x_2(p), \cdots, x_m(p)\}$, expected output at the output layer: $Y(p) = \{y_1(p), y_2(p), \cdots, y_m(p)\}$, which means the low-altitude safety level. Then the input and output of the hidden layer are obtained as follows:

$$\frac{\partial L}{\partial \omega^2_{ij}}=\frac{\partial L}{\partial s^2{}_j}\bullet\frac{\partial s^2}{\partial \omega^1{}_{ij}} \tag{15}$$

$$y_{hj}(p)=\theta^1(s^1{}_j(p))\,j=1,2,\cdots,n \tag{16}$$

2) The input and output of the output layer are obtained respectively as below:

$$s^2{}_j(p)=\sum_{i=1}^{n}\omega^2{}_{ij}\bullet ho_i(p)-B_y\,j=1,2,\cdots,k \tag{17}$$

$$y_j(p)=\theta^2(s^2{}_j(p))\,j=1,2,\cdots,k \tag{18}$$

where ω^2_{ij} is the connection weight of the output layer, By represents the threshold of the output layer, and θ^2 is the function of the output layer.

3) The error of low-altitude safety level evaluation is acquired according to the output expected value and the actual value estimated by the BP neural network, and the partial derivative of the output layer is solved on this basis as follows:

$$\frac{\partial L}{\partial \omega^2_{ij}}=\frac{\partial L}{\partial s^2{}_j}\bullet\frac{\partial s_j{}^2}{\partial \omega^2{}_{ij}} \tag{19}$$

4) The partial derivative of the hidden layer is solved per the output layer and ω^2_{ij} of the hidden layer as follows:

$$E=\frac{1}{2S}\sum_{p=1}^{s}\sum_{j=1}^{k}(y_j(p)-y_j(p))^2 \tag{20}$$

5) Corresponding adjustments are made on ω^1_{ij} and ω^2_{ij}, and the global error of low-altitude safety level evaluation is calculated as:

$$E=\frac{1}{2S}\sum_{p=1}^{s}\sum_{j=1}^{k}(y_j(p)-y_j(p))^2 \tag{21}$$

where S stands for the number of samples included in the low-altitude safety level evaluation.

6) If the error of the low-altitude safety level evaluation meets requirements, then the BP neural network will stop training; otherwise, training will be continued by returning to Step 5.

7) The low-altitude safety level evaluation result of the BP neural network is output.

4. Results analysis and discussion

4.1 Data sources

In this study, the texts of government sectors, emergency management regulations, typical accident cases, and related documents were mined. The evaluation indexes of low-altitude flight safety were established by referring to policy documents, such as the Opinions on Deepening Low-altitude Airspace Management Reform in China, A Notice of the State Council on Printing and Distributing the "14th Five-year" National Emergency System Plan, and Regulations on

Low-altitude Flight Safety [22-23], as well as 58 periodical documents from the Web of Science and CNKI.

4.2 Extraction of evaluation indexes for low-altitude flight safety

Based on safety systems engineering theory, and tailored to the characteristics of low-altitude flights, a new evaluation index system for low-altitude flight safety was established, focusing on four aspects: “human-machine-environment-management.” Given that human factors are the main source of low-altitude flight safety accidents, they were regarded as the main participants in low-altitude flight safety operation. These factors include six indexes: passengers’ physical condition, passengers’ safety awareness, passengers’ psychological quality, pilots’ flight experience, passengers’ illegal operation, and pilots’ illegal operation. Ensuring the normal operation of equipment is the key to safety. The machine level includes six indexes: equipment maintenance and updating, electric power and propulsion system, communication and navigation equipment, and safety and protective equipment. In terms of environmental factors, five indexes are the key factors affecting flight safety: bad weather, complex terrain, low-altitude obstacles, disturbance signals, and flow density. Finally, six management indexes are included: laws and regulations, enterprise supervision, rescue plan, emergency organizations, rules and regulations, and training and drills. Fig. 3 below illustrates the evaluation index system used in this study.

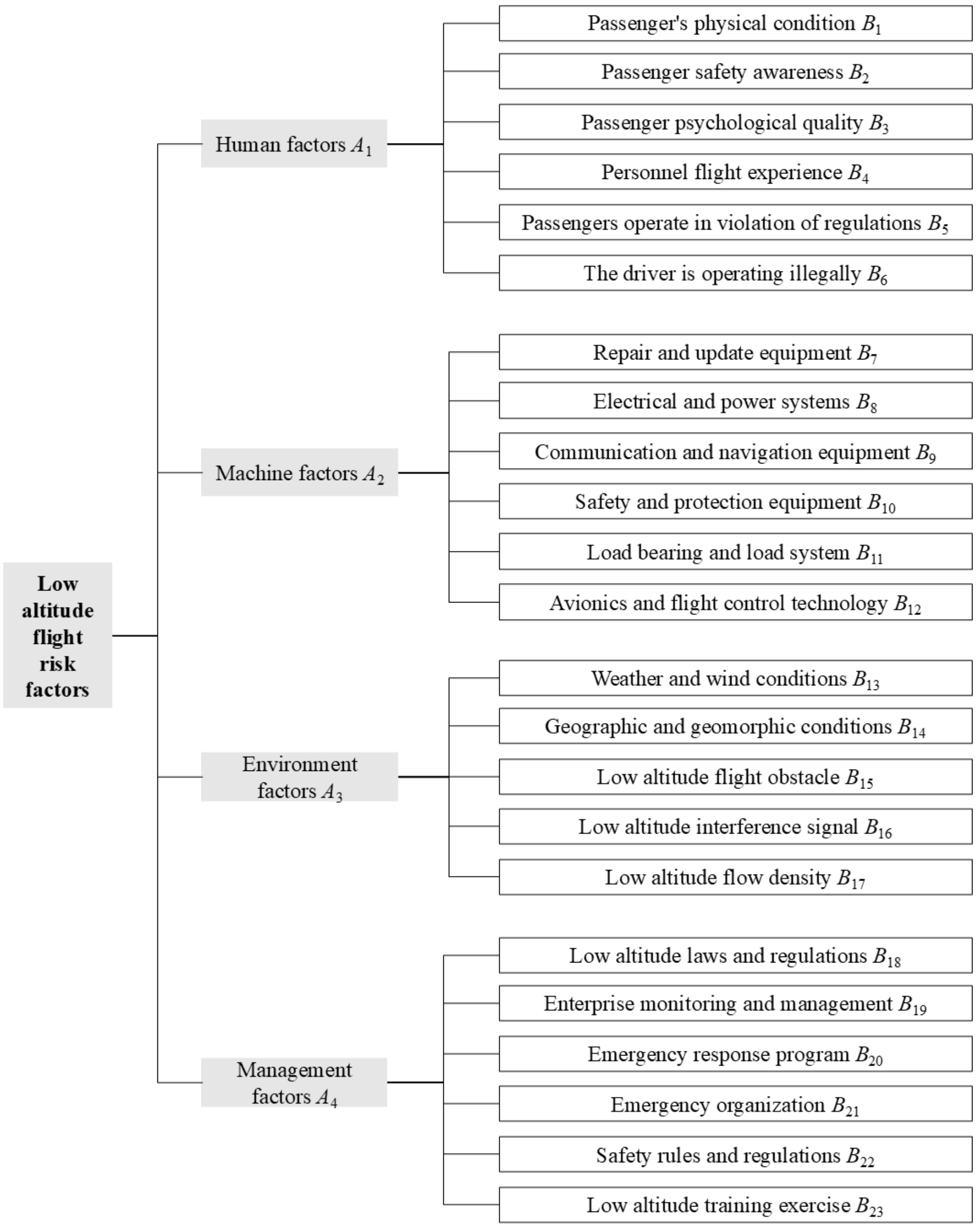

Fig. 3. Evaluation index system for low-altitude flight safety

Low-altitude aircraft include hot air balloons, airships, airplanes, gliders, rotorcrafts, helicopters, and so on. Through e-mail, telephone, video, and on-the-spot interviews, this study carried out a questionnaire survey on risk management among machinery manufacturing enterprises, such as paragliders and roller coasters; limited liability companies, such as AVIC General Aircraft; low-altitude flight operation enterprises; and scholars engaged in low-altitude flight safety operation research. Next, the reliability and validity of the initial questionnaire were further tested based on the data of a large sample size [24]. The Cronbach’s α coefficient of the questionnaire was 0.864, and those of each dimension were 0.817, 0.917, 0.943, 0.835, 0.928, and 0.916, respectively. The content validity index (I-

CVI) at the item level was 0.82–1.00, and the content validity index (S-CVI) at the scale level was 0.95. Three common factors were extracted through exploratory factor analysis, and the cumulative contribution rate of variance was 62.308%, indicating that the measurement structure has good reliability, validity, and equivalence. Furthermore, the key risk factors for low-altitude flight safety were determined using the LEC risk identification method in combination with the questionnaire survey result. The values of L, E, and C were determined based on the questionnaire survey results, and the key risk factors were identified based on the LEC risk assessment method, as shown in Table 1.

Table 1. Identification of key risk factors in low-altitude flights and risk evaluation

One grade index evaluation	Two grade index evaluation	LEC risk evaluation				Key risk factors	
		L	*E*	*C*	*D*	Yes	No
Human factors A_1	Passenger's physical condition B_1	2	6	3	36		√
	Passenger safety awareness B_2	3	2	6	36		√
	Passenger psychological quality B_3	2	3	30	180	√	
	Personnel flight experience B_4	2	3	30	180	√	
	Passengers operate in violation of regulations B_5	2	3	30	180	√	
	The driver is operating illegally B_6	1	6	3	18		√
Machine factors A_2	Repair and update equipment B_7	1	6	40	240	√	
	Electrical and power systems B_8	3	2	6	36		√
	Communication and navigation equipment B_9	3	2	6	36		√
	Safety and protection equipment B_{10}	3	3	15	135	√	
	Load bearing and load system B_{11}	1	6	3	18		√
	Avionics and flight control technology B_{12}	1	2	6	12		√
Environment factors A_3	Weather and wind conditions B_{13}	3	3	15	135	√	
	Geographic and geomorphic conditions B_{14}	1	6	7	42		√
	Low altitude flight obstacle B_{15}	1	6	30	180	√	
	Low altitude interference signal B_{16}	1	6	7	42		√
	Low altitude flow density B_{17}	1	6	3	18		√
Management factors A_4	Low altitude laws and regulations B_{18}	1	3	7	21		√
	Enterprise monitoring and management B_{19}	1	6	40	240	√	
	Emergency response program B_{20}	1	6	3	18		√
	Emergency organization B_{21}	1	6	40	240	√	
	Safety rules and regulations B_{22}	1	6	7	42		√
	Low altitude training exercise B_{23}	1	6	40	240	√	

Table 1 presents the 10 risk indexes for the key risk factors for low-altitude flight safety determined based on the LEC risk identification method. The risk factors include passengers' psychological quality, personnel flight experience, passengers' illegal operation, equipment maintenance and updating, safety and protective equipment, weather and wind direction conditions, low-altitude flight obstacles, enterprise supervision, emergency organizations, and low-altitude training and drills, all of which are shown in Fig. 4.

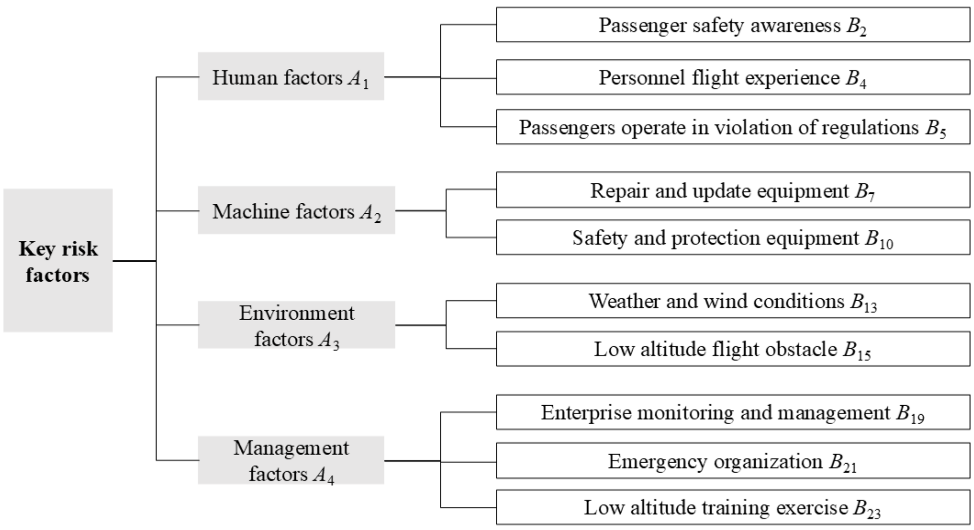

Fig. 4. Key risk factors of low-altitude flights

4.3 Demarcation of low-altitude flight safety evaluation level

The evaluation result of low-altitude flight safety was divided into five levels: [0–20] unsafe, [20–60] relatively unsafe, [60–75] generally safe, [75–90] relatively safe, and [90–100] safe. Table 2 below shows the evaluation levels of low-altitude flight safety.

Table 2. Evaluation levels of low-altitude flight safety

Grade	Unsafety	Less safe	Ordinary safe	Rather safe	Safe
Section	[0,20)	[20,60)	[60,75)	[75,90)	[90,100)

4.4 Weight determination for key risk factors of low-altitude flights

The weight values of the key risk factors in the project were determined through the questionnaire survey and on-the-spot investigation of the enterprise layer, management, passengers, and related safety emergency experts of a low-altitude flight operation project. Table 3 shows the index weight values of this project based on the combination weighting algorithm of game theory using the correlation weighting and difficulty weighting of evaluation indexes.

Table 3. Weight values of key evaluation indexes for low-altitude flights

One grade index evaluation	Two grade index evaluation	Relevance weight value	Difficulty weighted weight value	Game theory combinatorial weights
Human factors A_1	Passenger safety awareness B_2	0.022	0.025	0.029
	Personnel flight experience B_4	0.233	0.224	0.244
	Passengers operate in violation of regulations B_5	0.021	0.034	0.025
Machine factors A_2	Repair and update equipment B_7	0.142	0.131	0.123
	Safety and protection equipment B_{10}	0.142	0.131	0.128
Environment factors A_3	Weather and wind conditions B_{13}	0.021	0.021	0.021
	Low altitude flight obstacle B_{15}	0.021	0.013	0.015
Management factors A_4	Enterprise monitoring and management B_{19}	0.213	0.232	0.214
	Emergency organization B_{21}	0.021	0.031	0.036
	Low altitude training exercise B_{23}	0.121	0.142	0.165

4.5 BP neural network design

In the evaluation index system for low-altitude flight safety, 10 key risk factors were determined: the input layer is the second-level index of low-altitude safety, the number of input neurons is 10, and the output is the prediction result of evaluation indexes. At present, there is no unified calculation method for the number of neurons in the hidden layer, which is generally calculated by an empirical formula: s = （m+n） 1/2+a, where m and n are the numbers of neurons in the input layer and output layer, respectively; a is generally 2–6; m = 10 and n = 10 are substituted into the formula; and the value of s is 6.7–10.7, taken as 7–11. According to the actual operation, the optimal number of nodes in the middle layer is generally about three-fourths of the number of nodes in the input layer [25]. Therefore, the number of nodes in the hidden layer is determined as 8, and the evaluation model is a BP neural network with a 10-8-10 structure. In simulating the BP neural network in this study, data training was implemented via the toolkit of MATLAB software. To ensure the accuracy of neural network prediction, hyperbolic tangent logsig function and linear purelin function were chosen as the activation functions and traingda as the training function.

4.6 BP neural network model training and testing

To improve the efficiency of solving index nonlinearity and verify the maturity of the network model, the BP neural network was divided into three sets: training, validation, and test. The training set mainly estimated the initial samples, the validation set verified the training performance of the network model, and the test set evaluated the sample data of the target program. Training set: The samples in the training set were randomly generated and divided by a proportion of 9:1. Owing to the diverse program types of low-altitude flights, a total of 30 programs, including 10 paraglider, 5 airship, 5 roller coaster, 5 parachuting, and 5 hot air ballon programs were selected, with 27 samples in the training set and 3 samples in the validation set. Both the diversity of low-altitude flight programs and data maturity were considered to improve the data reference. In this study, 10 experts were invited to score the evaluation indexes of the 30 programs. The related data of scoring questionnaires and low-altitude flight programs were simultaneously sent to the 10 experts. The score range of each evaluation index was 0–100, with higher scores indicating the better safety problem represented by this index, and lower scores indicating the poorer safety problem represented by the index. The score of each safety index was multiplied by the index weight value in Table 3, followed by the weighting operation to calculate the final score of index. The data of training samples are listed in Table 4 below.

Table 4. Training sample data

Training sample	B_2	B_4	B_5	B_7	B_{10}	B_{13}	B_{15}	B_{19}	B_{21}	B_{23}
1	89	78	90	90	89	85	85	85	85	85
2	87	98	86	68	76	74	84	73	91	74
3	76	89	67	70	78	78	78	87	98	86
4	98	76	86	78	76	79	79	85	85	85
5	76	69	67	60	69	83	83	63	76	89
27	95	84	94	95	95	85	98	90	90	87

A total of 27 groups of data of training samples were imported into the MATLAB workspace, and the number of error fitting times of training sample data was set to 10, with the maximum epoch number of 9,999 and the learning efficiency of 0.01. In the operation training of the whole network, training was terminated only if one of the following requirements was satisfied: non-convergence occurred 10 consecutive times in the fitting training, the set maximum number of epochs was reached, or the training accuracy was smaller than or equal to 0.001. The training results are displayed in Fig. 5.

Fig. 5 reveals that after 3,608 training iterations, the BP neural network reached convergence. The data from three validation sets, listed in Table 5, were imported into the BP neural network to verify its accuracy and feasibility. The output results are displayed in Fig. 6 and 7 below.

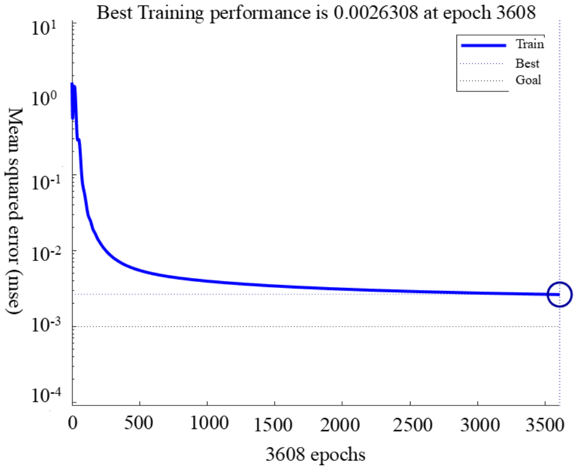

Fig. 5. Mean square error curve of BP neural network training

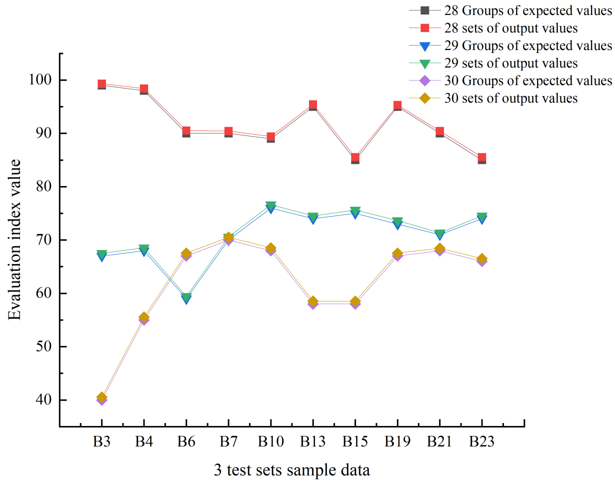

Fig. 6. Expected value and output value of three groups of validation sets

Table 5. Validation sample data

Validation sample	B_2	B_4	B_5	B_7	B_{10}	B_{13}	B_{15}	B_{19}	B_{21}	B_{23}
28	99	98	90	90	89	95	85	95	90	85
29	67	68	59	70	76	74	75	73	71	74
30	40	55	67	70	68	58	58	67	68	66

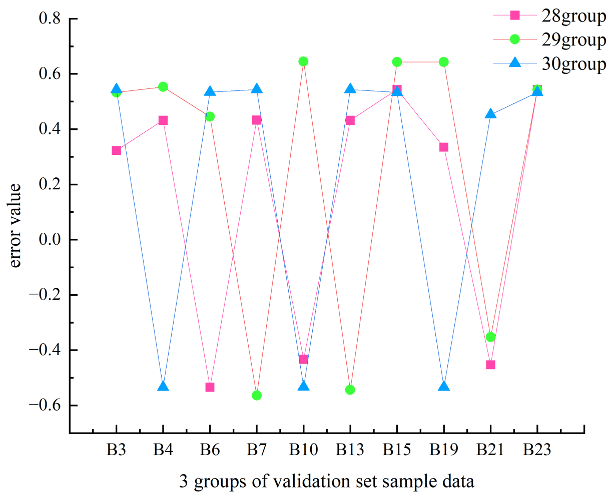

Fig. 7. Error between expected value and output value of three groups of validation sets

Fig. 6 shows that the broken line for the expected value of the three groups of validation sets coincide with that of the output value of the BP neural network. Fig. 7 reveals that the calculated error value of the three groups of validation sets was always smaller than 0.1, showing that the network trained by the first 27 groups of samples achieved a good evaluation effect.

4.7 Case analysis

The safety indexes of the Fuxishan paragliding program in Zhengzhou, Henan Province, combining the enterprise level, management, and passengers, were scored. The input neurons of the BP neural network were X = 58, 60, 61, 67, 58, 63, 58, 59, 59, and 60, and the output values were Y = 58.543, 60.432, 61.754, 65.765, 59.422, 63.632, 57.753, 59.742, 60.211, and 60.311, respectively. From the output results, 10 evaluation results were close, with values ranging from 58 to 64, the maximum value was 63.632, and the minimum value was 58.543. According to the safety level intervals in Table 2, the safety level of the paragliding program was relatively unsafe. In particular, its score of psychological quality was the lowest (58.543), indicating that the psychological quality of passengers is the key to improving the safety level of the program. This was followed by the scores of safety and protective equipment, low-altitude emergency organizations and low-altitude training and drills. The result further revealed that the three evaluation indexes are the key factors elevating the safety level of this program. When evaluating the safety level of other low-altitude flight programs, the input samples were imported into the trained mature network according to the index scoring of this low-altitude flight program, thus rapidly and scientifically realizing dynamic safety evaluation.

5. Conclusion

To address the risk factors and safety evaluation issues associated with the safe operation of low-altitude flights, this study applied a game-theory-based combination weighting method and BP neural network approach. Key risk factors for low-altitude flights were identified, a safety risk evaluation model was constructed, and the weight values of critical risk indicators were determined. The safety level was evaluated using the BP neural network model. The following conclusions were drawn:

1) In this study, the safety of the Fuxi Mountain paragliding project in Zhengzhou, Henan province, was evaluated using the game-theory-based combination weighting method and BP neural network algorithm. The LEC method was applied to identify the critical risk factors for low-altitude flight safety. The weights of these factors were determined based on the game-theory-based combination weighting method, and the BP neural network model was employed to quantitatively analyze the safety level of the project.

2) The BP neural network output indicated that the maximum value for the Fuxi Mountain paragliding project was 63.632, and the minimum value was 58.543, corresponding to a safety level classified as "relatively

unsafe.” Factors such as tourist psychological resilience, safety and protective equipment, emergency response agencies, and training drills for low-altitude flights received relatively low scores. These results provide strategic guidance for improving the safety level of low-altitude flight operations.

3) The integrated game-theory-based combination weighting and BP neural network method for low-altitude flight safety evaluation can balance the conflicts among evaluation indicators while incorporating comprehensive information. By leveraging the dynamism and precision of the BP neural network, this method reduces subjectivity in calculating indicator weights and generates objective, quantitative results. Therefore, it is a feasible approach for evaluating the safety of low-altitude flights.

In summary, the game-theory-based combination weighting and BP neural network method for low-altitude flight risk identification and safety evaluation clarifies key risk factors, emphasizes improvements in safety-related factors, and strengthens risk management. The proposed evaluation model combines a safety risk index system with the game-theory-based combination weighting and BP neural network algorithm, reducing the scoring subjectivity and providing accurate support for low-altitude flight risk prevention. However, due to limitations in sample data, a more comprehensive and systematic framework of safety evaluation indicators needs to be established, which will be the focus of future study.

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