A Knowledge-Data-Driven Emergency Decision Support Method for Aviation Support Operation Risk

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Abstract. The aviation support system is the core of ensuring the safe takeoff and landing of aircraft and orderly operation. However, when the aviation support task is carried out, there are many factors leading to disasters, with a wide range of impacts, leading to difficult safety management. Therefore, it is necessary to avoid the occurrence of risks and quickly curb the spread of risks. In view of the problems of high timeliness and complexity of aviation support operation risk decision-making, the characteristic attributes of three parts of the disposal process are given through the analysis of the decision-making process. A knowledge-data-driven emergency decision support method for aviation support operation risk, based on case-based reasoning and rule-based reasoning is proposed, which can quickly generate effective decision schemes. With the verification of 20 cases of aviation support operation risk, the performance of the hybrid method was better than pure CBR or RBR.

Keywords: Case-based Reasoning · Rule-based Reasoning · Aviation Support System · Risk Analysis · Emergency Decision

1 Introduction

The aviation support system (ASS) is a typical large-scale discrete event dynamic complex system [1], which mainly completes the tasks of aircraft takeoff, landing, lifting, transfer, parking and supply. ASS involves the complex coupling of multiple elements such as mission, personnel, equipment and environment. It is the key system that affects the aircraft dispatch capability and efficiency [2].

The aviation support operation has the characteristics of strong constraints and high randomness. It is an important and complex task to schedule and make decisions for the operation. Luo, Y. [1], Ding, G. [3] completed the description of the aviation support operation and evaluated the support capability through modeling and simulation; Yang, F. [4] established a flight operation model based on network theory to analyze the functional integrity of the network. However, when unplanned random events occur during the support operation, such as equipment damage, lack of resources, and landing failure,

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the established support mission process will be directly disrupted. Then series of chain reactions appear to affect the smooth progress of the ASS. Making effective decisions in real-time and accurately in emergencies is a major test for support personnel. Therefore, it is the emerging demand of ASS to assist decision makers through intelligent methods.

In order to meet the needs of real-time and targeted decision-making, the current research on intelligent decision-support methods for sudden risks mainly focuses on two technologies: ① Case-based Reasoning (CBR), which takes similar historical problems as a reference for current decision-making problems. But it is difficult to encounter exactly the same problems in reality, and the accuracy of the methods is insufficient; ② Rule-based Reasoning (RBR), which reasons decision schemes based on expert rules, has the characteristics of accurate and effective decision-making. But it takes a lot of manpower to acquire knowledge and write rules. Prentzas et al. [5] believed that rules represent general knowledge in a field, while cases represent specific knowledge. The integration of the two can make up for their shortcomings. There are four common combination methods: (1) RBR-first and CBR-last [6]; (2) CBR-first and RBR-last [7]; (3) CBR-RBR parallel [8]; (4) Combination of RBR and CBR [9]. Rossille [6] used the method of RBR-first and CBR-last to improve the retrieval performance by comparing patients' cases with corresponding guidelines and then with past cases. Yang, M. et al. [7] used the method of CBR-first and RBR-last to retrieve similar cases for learning. Through the rules integrated into the CBR process, the retrieval performance is improved by dynamically adjusting the attribute weight. Zhang, T. [9] proposed a combined approach to provide professional and effective solutions for sudden water environmental pollution. The risk of aviation support operations is sudden and uncertain, while the number of historical cases that can be used is small. In order to provide better decision support for the aviation support system, this paper proposed a knowledge-data-driven emergency decision support method for aviation support operation risk. The corresponding feature attribute representation knowledge method is established by analyzing the risk event and its disposal process. The method of RBR-first and CBR-last is verified to generate effective decision scheme.

2 Analysis of Aviation Support Operation Risk

2.1 Aviation Support Operation Risk

The risk of aviation support operation refers to the sudden occurrence of natural disasters, human errors, equipment failures and other events during the aviation support operation, which may affect normal operation and threaten the safety of people's lives and property. The landing and take-off stages of aircraft are the periods of the high incidence of accidents. This period accounts for about 4% of the whole task time, and the accident rate accounts for more than 60% of all accidents [10]. Therefore, the prediction and disposal of the aviation support operation risk is an important part of the risk management. As shown in Fig. 1, it is the risk of some high-risk aviation support tasks.

2.2 Characteristics of Aviation Support Operation Risk

To meet the real-time and targeted needs of decision-making, it is necessary to extract the current situation information for judgment and analysis as the information basis

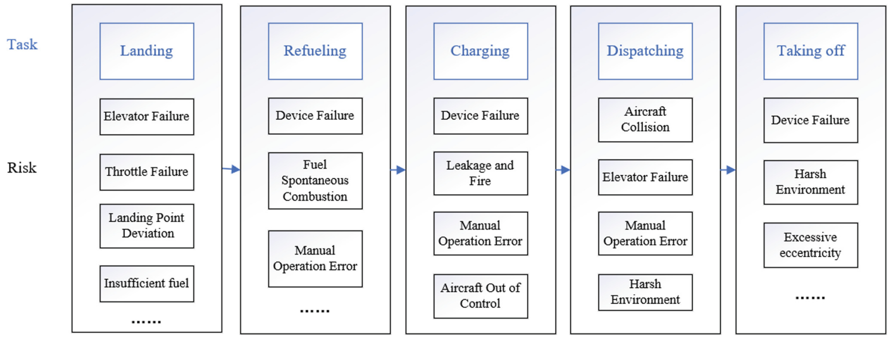

Fig. 1. Aviation support operations risk

for decision-making. From the perspective of risk decision-making and disposal, the situation elements of decision-making must include three parts: the basic situation of risk, decision-making and disposal, and disposal results. Therefore, the situation elements are represented by triplets.

(1) Basic risk information:

The description of the current situation information of the risk, including the time, location, risk type, risk level, weather conditions, etc. As shown in the Table 1.

(2) Decision-making and disposal:

Resources to be dispatched and measures to be taken to deal with risks, including the personnel team to be dispatched, the professional equipment to be used, the emergency supplies to be dispatched, and the work done by the personnel involved in disposal.

(3) Disposal results:

The final loss caused by the risk, and the evaluation of the risk and risk disposal.

Table 1. The description of the current situation information of the risk

Attribute	Concrete content
Time	Date and specific time of risk
Place	Location of the accident (a support position)
Type	Landing failure, etc.
Level	Particularly major risks, major risks, general risks and low risk
Aircraft	Type, oil quantity, etc.
Weather	Wind, rainfall, temperature, visibility and other conditions
Surroundings	Distance from land, secondary disasters, etc.

3 Decision Support Methods for ASS Risks

3.1 Knowledge-Data-Driven Emergency Decision Support Method

The traditional aviation support operation risk decision usually depends on the experience and judgment of the decision-maker. This model has two disadvantages: ① The relatively passive way of receiving information and the limited amount of information received, which leads to the slow efficiency of acquisition and processing, resulting in the inadequate utilization of the big data of the aviation support system; ② It is easy to misjudge unconventional events, which requires a high level of decision makers. "Knowledge-driven" and "data-driven" are complementary. The data-driven method has ability to induction, while the knowledge-driven method has the ability of reasoning and cognition. Therefore, this paper proposes a knowledge-data-driven emergency decision support method, which combines a large amount of data and empirical knowledge to provide reliable and efficient support for decision-making.

Figure 2 shows the generation process of the decision-making scheme. When the risk situation information is obtained, the decision-making scheme is first reasoned according to the knowledge rules. If there is no matching scheme, case reasoning is used for similarity matching. Then the rule reasoning can be performed according to the current case attribute and the historical case attribute to realize the correction and optimization of the decision-making scheme.

The workflow is as follows:

(1) Collect current situation information through sensor equipment or user interaction interface;
(2) Pre-process according to the basic risk information and divide it into different types of sets;

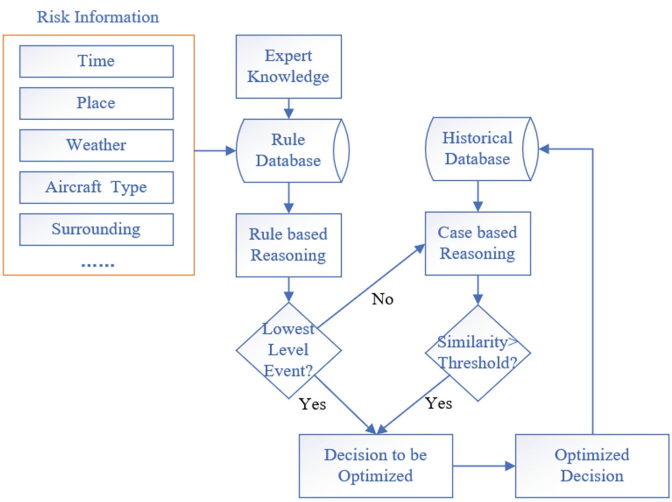

Fig. 2. The generation process of the decision-making scheme

(3) Call the corresponding rule base to match and reason according to the attributes of the current risk event until the decision scheme is obtained and go to step (6), otherwise go to step (4);
(4) Case-based reasoning based on the risk situation information to obtain historical cases higher than the similarity threshold, then generate the decision scheme to be optimized;
(5) According to the attributes of the current case situation, rule reasoning to revise and generate an optimized decision scheme;
(6) Output the decision scheme, supplement the rule base through expert correction according to the final implementation plan.

3.2 Knowledge-Driven Decision Support Method

The essence of rule-based reasoning is an expert system based on rules. Its core is to perform specified operations when facts meet the rules. Generally, production rules are used to express the heuristic experience of experts. The general form of rules is:

IF condition 1 AND condition 2 AND …

THEN conclusion.

The rules in the rule base are in the form of IF antecedent and THEN consequent. The IF antecedent is the basic situation of aircraft type, location, weather and other risks, and the THEN consequent is the decision scheme. The reasoning and decision-making process is as follows:

(1) Input characteristic attributes and preprocess. Classify risk types according to the basic risk information to reduce the complexity of rule reasoning. Call the corresponding rule base for reasoning and output the decision scheme;
(2) If there are multiple rules matching, resolve the conflict. Sort according to the pertinence of the rules and choose the rules of more antecedent for reasoning.

3.3 Knowledge-Driven Decision Support Method

The essence of CBR is reuse. The similarity matching algorithm is used to match the current case to be decided with the historical case. The definition $sim(C_0, C_j)$ represents the similarity of current aviation support operation risk C_0 and the known risk C_j in the case library, $sim(C_0, C_j) \in (0, 1)$. Closer to 1, the basic situation of the two risks is more similar. μ is defined as the similarity threshold. When the similarity is larger than the threshold, it will be output. When there are multiple cases whose similarity is larger than the threshold, they will be sorted and displayed according to the similarity. The calculation method is as follows:

(1) Enumerated properties

Enumerative properties list all possible values of this property. There is no real relationship of the differences between different property values, Such as the category or level of risk. The calculation method of similarity is as follows:

$$sim(C_{0i}, C_{ji}) = \begin{cases} 0, C_{0i} \neq C_{ji} \\ 1, C_{0i} = C_{ji} \end{cases} \tag{1}$$

(2) Numeric properties

Numeric properties can be expressed with certainty by numerical values, such as temperature, wind speed, etc. Their similarity can be calculated by distance-based method. The most commonly used is European distance. The algorithm is as follows:

$$sim\left(C_{0i}, C_{ji}\right) = 1 - \frac{d\left(C_{0i}, C_{ji}\right)}{z_i} = 1 - \frac{|C_{0i} - C_{ji}|}{z_i} \tag{2}$$

where, z_i represents the value range of the i th property.

(3) Fuzzy properties

Fuzzy properties are conceptual, such as the evaluation of risk disposal effect (very good, good, average, poor, very poor). So first convert the fuzzy attribute value to triangular fuzzy number by formulas (3) and (4):

$$C_{0i} = (l_{0i}, m_{0i}, u_{0i}) \tag{3}$$

$$sim\left(C_{0i}, C_{ji}\right) = \exp[-\frac{\sqrt{(l_{0i} - l_{ji})^2 + (m_{0i} - m_{ji})^2 + (u_{0i} - u_{ji})^2}}{\sqrt{(l_{imax} - l_{imin})^2 + (m_{imax} - m_{imin})^2 (u_{imax} - u_{imin})^2}}] \tag{4}$$

where, l_{imax} represents the maximum value of the lower limit of n triangular fuzzy numbers corresponding to the i th property, l_{imin} represents the minimum value of the lower limit of n triangular fuzzy numbers corresponding to the i th property.

Then according to the attribute weight w_i calculated by AHP, calculate the overall similarity between aviation support operation risk and historical cases by formula (5):

$$Sim\left(C_0, C_j\right) = \sum_{i=1}^{n} \left(\frac{w_i}{W_{C_0 \wedge C_j}} sim\left(C_{0i}, C_{ji}\right)\right) \tag{5}$$

4 Case Study

Taking the wave-off decision as an example, the specific information of the case to be decided is shown in Table 2, and the generated decision scheme is shown in Table 3. Because the aircraft parameters are within the wave-off boundary, it can be concluded through rule reasoning that the aircraft can land, but the effect is general. Since the time is night and the pilot level is good in the historical case with the highest matching degree, the result of case reasoning is wave-off, with good effect. The output result after correction is wave-off, and the effect is average.

To verify the effectiveness of the method proposed in this paper, 20 historical landing failure cases are selected. RBR, CBR and combined methods are respectively used to generate decision schemes. After comparing generated decision schemes with the results recommended by experts, precision, recall and F1 value are used to evaluate

Table 2. Basic information

Attribute	Concrete content
Time	2018-10-23 18:43
Type	Landing
Level	General risk
Aircraft situation	Lateral landing deviation: 5.6 m; Landing speed: 70 m/s; The clearance at the stern of the ship: 3.3 m
Pilot level	General
Weather	Wind force: 2; Temperature: 15; Good vision

Table 3. Output

Method	RBR	CBR	RBR + CBR
Output (scheme, evaluation)	Land, general	Wave-off, great	Wave-off, general

three methods. Precision represents the accuracy of the algorithm, and the recall rate is a measure of integrity. F1 value is the comprehensive evaluation standard of the two indicators. This paper selected these three indicators to evaluate the effectiveness of the knowledge-based data-driven decision support method. The closer the three indicators are, the more effective the method is. The formula of the three indicators is as follows:

$$\text{precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{recall} = \frac{TP}{TP + FN} \tag{7}$$

$$\text{F1} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}} \tag{8}$$

where, TP, FP and FN indicate correct hit, false alarm and missing alarm.

Figure 3 shows the average precision, recall and F1 value of different methods. The average precision, recall and F1 value of pure RBR are 82.9%, 67.6% and 74.2%, while the average precision, recall and F1 value of pure CBR are 78.2%, 75.9% and 77.7%. By combining RBR and CBR, the retrieval performance significantly improved. The average precision, recall and F1 value of CBR-RBR are 90.4%, 80.2% and 84.7%. Because of the complex risk information of part cases and limited historical cases and expert rules, they cannot cover all cases, resulting in many false alarms and missing alarms. The performance of the method proposed in this paper is relatively stable, and the ability to retrieve correct decision schemes is significantly improved, which can effectively assist decision makers in handling aviation support operation risk.

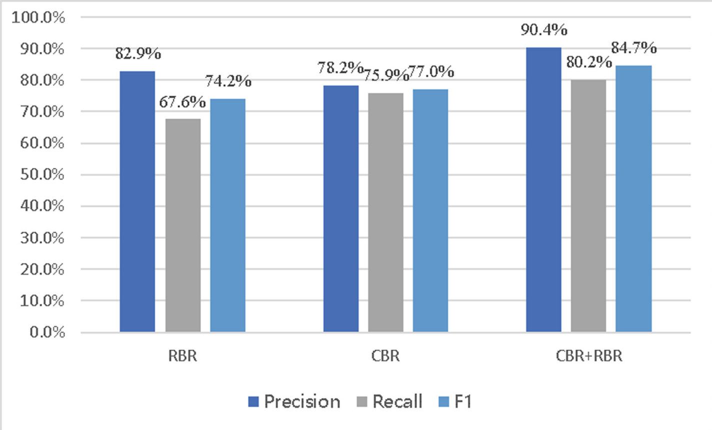

Fig. 3. Precision, recall and F1 value of different method

5 Conclusions

This paper analyzes the characteristics of aviation support operation risk and introduces a knowledge-data-driven emergency decision support method for aviation support operation risk. Based on the analysis of the support process and risk characteristics, the characteristic attribute representation method of the basic risk situation, the disposal process and the disposal effect are given. The reasoning method combining RBR and CBR is discussed, and the corresponding decision scheme generation process is given. The method proposed in this paper is verified by cases of aviation support operation risk, which can ease the burden of decision makers.

In this paper, the representation of risk is not standardized enough well, and the description of the risk disposal process is simplified, which affects the accuracy and implementation effect of the final reasoning. In terms of decision support methods, RBR and CBR can be better combined. And more artificial intelligence methods can be used to solve the decision-support problems of ASS more intelligently and efficiently.

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