Air Traffic Safety Risk Assessment based on Rough Set and BP Neural Network

Lan Ma*, Weian Li and Zengxian Geng
Air Traffic Management College,
Civil Aviation University of China, Tianjin, China

Keywords: Air Traffic Safety, Rough Set, Attribute Reduction, BP Neural Network.

Abstract: The safety of air traffic control is an important link in the safety system of civil aviation industry. In order to evaluate the safety risk of air traffic control in a more comprehensive and reliable way, proposing an air traffic safety risk modeling and evaluation method based on rough set and BP neural network. After analyzing the factors that may affect the safety in the actual work of ATC, 24 attribute variables which can measure the safety risk of ATC are given. Aiming at the shortcomings of traditional neural network training with high redundancy, slow convergence and easy to fall into local optimum, the attribute reduction method is used to reduce the input attribute by rough set theory. Under the premise of not affecting the training results and the accuracy of the data, removing the low correlation attributes with the results, the network structure is simplified, the training times are reduced, and the training speed and accuracy of the neural network are improved. Use the simplified condition attributes of the original data after rough attribute reduction as input data, the conflict resolution object is as output data, using MATLAB to build the neural network, and the trained network is tested and verified to be reliable. Compared with the model before the reduction of the initial data, significantly improves the accuracy and efficiency. The model is verified by examples The results show that the combination of rough set and BP neural network can accurately evaluate the risk of air traffic control, change the risk assessment from qualitative to quantitative, and provide guidance for the actual operation.

1 INTRODUCTION

The unsafe incidents in civil aviation operations can be divided into five categories: aircraft operation, aircraft maintenance, ground support, airport operations and ATC safeguards. It can be seen that some of the unsafe incidents are related to ATM system. Air Traffic Management System is an important part of the civil aviation system. It is also a complex system of structural correlation. In recent years, air traffic control accidents such as runway incidents caused by security problems are common. In order to ensure the safe operation of civil aviation system, it is crucial to assess the air traffic safety risk (Zellweger and Donohue 2015).

* Ma Lan, female, Civil Aviation University of China, Associate Professor, Ph.D. major research area: Transportation planning, air traffic control information processing.

1.1 Research Status

As people pay more attention to the safety of ATC, more and more scholars inland and abroad are engaged in the research of ATC safety, and they have achieved some results. In the 1990s, academics in the United States and European countries started to study the theory of civil aviation safety risk management. Shyur (2008) quantified the aviation risk caused by human error with studying aviation accidents and safety indicators. The benchmark risk function was taken into aviation risk evaluation as the quadratic function, then get a proportional risk model to investigate non-linear aviation safety factors and evaluate aviation risk; Al Basman and Hu (2012) have studied the theory of stochastic safety analysis that can be used in ATC systems and proposed two ways that a multi-level Markov chain and air traffic flow assessment to solve the safety issues in the ATC environment; Cruck and Lygeros (2015) have built a hybrid model which can be man-

Ma, L., Li, W. and Geng, Z.
Air Traffic Safety Risk Assessment based on Rough Set and BP Neural Network.
DOI: 10.5220/0006889008630870
In *Proceedings of the 13th International Conference on Software Technologies (ICSOFT 2018)*, pages 863-870
ISBN: 978-989-758-320-9

machine interaction, this model can be used in complex situations to forecast, in order to percept air traffic safety risk.

Domestic research on ATC safety risks started a little later than abroad. However, in recent years there have been some achievements. Many scholars have used Bayesian analysis (Liao et al. 2015), gray-level analysis(Guo et al. 2015), matter-element analysis theory (Zhang et al. 2016) and other methods to study the ATM safety problems. Based on the analysis of triangular fuzzy mathematics and ANP principle, Du et al. (2010) have established an air traffic control security risk assessment model with Fuzzy-ANP in view of the interaction of security risk factors; China's civil aviation industry now put forward the safety management system (SMS) whose core is risk management to control the security risk through the overall operation of the various links (Lu 2017).

1.2 Introduction

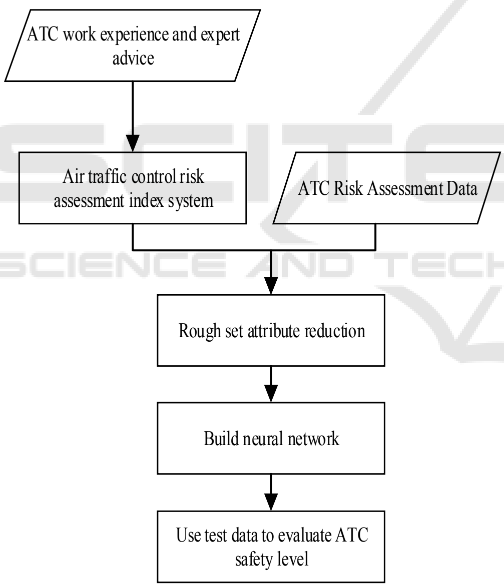

Figure 1: Research content and process.

This paper combines and draws on the advantages of the existing researches, and on this basis expands and builds the risk assessment index system. Then it extends the qualitative research to quantitative research that can be more universal, and using rough set theory with attribute reduction function makes the neural network model structure (Wang 2013) more concise, and makes the forecasting results fast and accurate. The research content and process is shown in figure 1.

2 CONSTRUCTION OF RISK ASSESSMENT INDEX SYSTEM

Based on a comprehensive analysis of the characteristics and significance of air traffic control system and its important position in the civil aviation industry, air traffic control risk assessment indicators (Luo et al. 2009) are generally divided into four categories: human factors, equipment factors, environmental factors and management factors The factors are the first layer of the whole index system, and then combine the examples of the ATC operation and the opinions given by the ATC experts. Each factor contains several sub-factors and they are evaluated as an indicator in the subsequent research. The final index system has the characteristics of science, and fits the actual work of the ATC. Air traffic control security risk assessment indicator system in Figure 4.

In order to analyze the impact of each indicator on the safety of ATC by means of qualitative and quantitative analysis, investigate the senior management of ATC system, controllers and ATC experts in the form of questionnaires. And ask them to combine their own actual work or research conditions, or assessment of an unsafe event, and mark each indicator based on their own knowledge and experience, scoring criteria: 1 point - very good, 2 points - good, 3 points - ordinary, 4 points - poor, 5 points - very poor. After marking the index, given the general

Evaluation of the security risk rating, there are five levels: level 1 is lowest risk, level 2 is lower risk, level 3 is medium risk, level 4 is higher risk, and level 5 is highest risk. Summarizing above work, the safety risk assessment system for ATC and the results of the questionnaire form the data foundation for the follow-up study in this paper.

3 INDEX REDUCTION BASED ON ROUGH SET THEORY

Rough set theory (Wang et al. 2009) is used to analyze and process data. It was first proposed by Polish mathematician Z. Pawlak in 1982, which has many advantages. It does not need too much raw data to find the hidden rules of data, it is now widely used in data mining, pattern recognition and other fields.

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

3.1 Rough Set Theory Applied to Air Traffic Control

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. In general, it is best to avoid acronyms in the abstract unless they are critical. Abbreviations such as IEEE, SI, MKS, CGS, SC, DC, and RMS do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

Obviously, the collated original data is too complicated to subsequent computational studies. Then we find that all the attributes are not equally important. There are some redundant or inconclusive attributes that can be eliminated, further obtaining a more streamlined and intuitive decision table.

Given R is a set of reduced attributes to be obtained, P is a set of condition attributes corresponding to 24 ATM safety risk assessment indicators, X is an instance set with removal compatibility examples, EXPECT is a termination condition for attribute dependencies, The following algorithm:

Initialize, make $R = core(C)$, $P = C - core(C)$, $k = 1$.

- Remove all compatible instances of U, that is:

$$X = U - POS_R(D) \tag{1}$$

- Calculation

$$k = \frac{card(POS_R(D))}{card(U)} \tag{2}$$

- if $k \geq EXPECT$, the algorithm terminates; otherwise, if $POS_R(D) = POS_C(D)$, returns

$$k = \frac{card(POS_C(D))}{card(U)} \tag{3}$$

the algorithm terminates;

- For any $p \in P$, calculation of

$$\upsilon_p = card\left(POS_{R\cup\{p\}}(D)\right) \tag{4}$$

$$m_p = \max\_size\left(POS_{R\cup\{p\}}(D)\right) / \left(R \cup \{P\} \cup D\right) \tag{5}$$

- For all $p \in P$, calculation $\upsilon_p \times m_p$ with the maximum value, and given $R = R \cup \{P\}$, $P = P - \{p\}$;

- Return to the first step

3.2 Data Attribute Reduction

In the study, 310 scoring surveys were conducted on the 24 safety risk assessment indicators of air traffic control. The final survey data constituted the domain U of the knowledge representation system, and then formed a complete decision table. The safety risk indicators {X1, X2, X3 , ..., X24} is the condition attribute, the security risk level is the decision attribute, the value of the attribute is 1, 2, 3, 4, 5, which meets the discretization requirements of the attribute reduction of the rough set. Show in table 1.

Table 1: Air traffic safety risk assessment decision table.

U	attribute C					attribute D
	X1	X2	X3	…	X24	safety risk level
1	1	3	1	…	2	1
2	3	1	2	…	1	3
3	4	1	2	…	2	2
4	3	1	1	…	1	3
…	…	…	…	…	…	…
310	2	1	2	…	2	1

The reducing result is usually not the only one. Finding all reductions or minimal reductions have proved to be an NP-hard problem. The general solution to this problem is heuristic search, which builds a reduced set of attributes by computing dependencies of attributes. And there are common attribute reduction methods like Johnson greedy algorithms and genetic algorithms.

For processing the original data, using Rosetta software to conduct attribute reduction, the software is table logic data tool based on rough set theory framework, it can be used to simplify the model. The processed data excel tables imported into Rosetta software for data complement and discretization. And select the method to reduce the data, then you can directly get attribute reduction results.

Table 2: Reduced air traffic safety risk assessment.

Factors	number	indicators
human factors	X1	Controller technical level is not up to standard
	X2	Controller psychological quality is not up to standard
	X3	Emergency response capacity is not enough
	X5	Controller or department head safety awareness and sense of responsibility is not enough
equipment factors	X7	Communication equipment is not working properly
	X8	Navigation device is not working properly
	X9	Monitoring equipment is not working properly
environ-ment factors	X13	Seat monitoring means imperfect
	X14	Scene monitoring and guidance system is not working properly
	X16	Weather conditions and weather disasters
manage-ment factors	X19	Poor management practices
	X20	Department of high frequency of conflict intensity
	X23	Safety education and training system is not perfect

After processing the data, the attributes after reduction are shown in Table 2, it can be seen that the attribute reduction obviously reduces the number of attributes from the original 24 to 13. To a certain extent, the reduction result also reflects the impact of various factors on the safety of ATC, showing that the most obvious impact of ATC safety is human factor.

4 AIR TRAFFIC CONTROL SECURITY RISK ASSESSMENT BY NEURAL NETWORK METHOD

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window in the formatting toolbar (Silva.et al. 2017).

4.1 Construction and Application of BP Neural Network based on Rough Set

Analyzing the reduction result of the safety risk indicators assessment data of ATC. It can be concluded that there is a certain causal relationship between the attributes and the final safety assessment, and the inherent law of the relation can be tapped by neural network (Liu et al. 2010) to get the quantitative and qualitative assessment of ATC risk assessment.

Aiming at the shortcomings of traditional neural network training with high redundancy, slow convergence and easy to fall into local optimum, the attribute reduction method is used to reduce the input attribute by rough set theory. Under the premise of not affecting the training results and the accuracy of the data, removing the low correlation attributes with the results, the network structure is simplified, the training times are reduced, and the training speed and accuracy of the neural network are improved.

For the general pattern recognition problem, adopting a three-layer neural network structure (Bruin et al. 2017). The following is the step of modeling the neural network of air traffic safety risk assessment(Ma and Chang 2017):

- Initialize weights, assign random values in the interval (0,1) to each connection weight and threshold;
- Determine the number of neurons in each layer, the number of neurons in the input layer is 13 attributes, the attribute values input after discretization;

- Determine the number of hidden layer neurons. In the three-layer network, choosing the number of hidden layer neurons is a very complex issue. It often requires designers' experience and multiple tests to determine. If the number of hidden layer neurons is n2, the number of input layer neurons is n1, the number of output layer neurons is m, choose the best n2 can refer to the following formula:

$$n_2 = \sqrt{n_1 + m} + a\,,$$

Where a is the constant between $\left[1,10\right]$;

$$n_2 = \log_2 n_1$$

However, the quantity is not fixed and needs to be constantly adjusted by the actual training test. In Table 3, the training errors when selecting different hidden layers are listed. Therefore, the number of hidden layer neurons is set as 9 in this study. Ensure the training accuracy and improve the computing speed.

Table 3: Implicit layer test error.

hidden layer neurons number	5	6	7	8	9
training errors	0.00350	0.00928	0.00300	0.00916	0.00122

- Choose transfer function. The transfer function of hidden layer neurons adopts S-type tangent function:

$$f\left(x\right) = \frac{2}{1+e^{-\alpha x}} - 1$$

Output layer neurons transfer function using S-type logarithmic function:

$$f\left(x\right) = \frac{1}{1+e^{-\alpha x}}$$

- The output layer should reflect the final five security risk assessment levels. In order to ensure the accuracy of the training results, we classify the levels as level 1 (1 0 0 0 0), level 2 (0 1 0 0 0), level 3 (0 0 1 0 0), level 4 (0 0 0 1 0), level 5 (0 0 0 0 1). Five neurons are set in the output layer to quantify the above five levels.

After modeling, the 310 groups of data are divided into training group and test group. The data are normalized by MATLAB (Ge and Sun 2007) and creating the complete network object by using the newff function in the toolbox. The training function trainlm uses Levenberg-Marquardt algorithm to train the network, after which you can set the training parameters in Table 4. Seen from Figure 2, after eight training, the network performance to meet the requirements, which is related to the network structure and learning rate.

Table 4: Training parameters.

training times	training goal	learning rate
1000	0.001	0.1

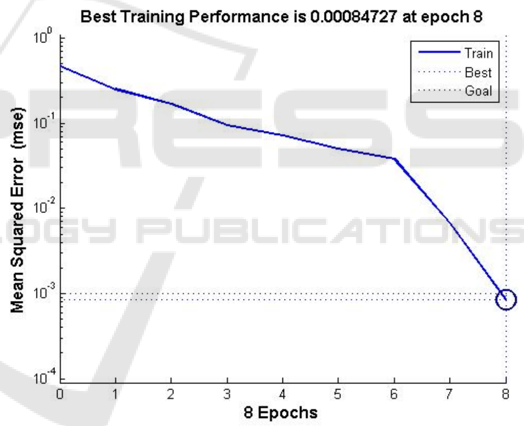

Figure 2: Training results.

4.2 Combination of Rough Sets and Neural Network Methods

Two variables were set for experiment, namely whether using the improved BP neural network and whether using the rough set theory was for data preprocessing. Then four experimental methods were formed and the four experimental methods were compared. The results are shown in Table5.

From the research results, we can know that using the rough set to reduce the attributes of the initial data can remove the redundant attributes and reduce the number of training sample attributes. Then the neural network structure is more concise and the operation time is reduced. The improved BP neural network is obviously superior to the BP neural network before in terms of time and accuracy. Combining rough set attribute reduction with neural network modeling can simplify the model structure and improve the operation efficiency and accuracy. It is a scientific and effective method to deal with such problems.

Table 5: Comparison of experimental methods.

Reduction	Improved	Training time	Number of iterations	Training error
No	Yes	80	1670	0.068
No	No	87	2000	0.14
Yes	Yes	24	668	0.018
Yes	No	41	1000	0.049

4.3 BP Neural Network Test

The neural network training of the data can be seen from Figure 3. After 668 trainings, the network performance has reached the requirements. It is related to the network structure and the learning rate.

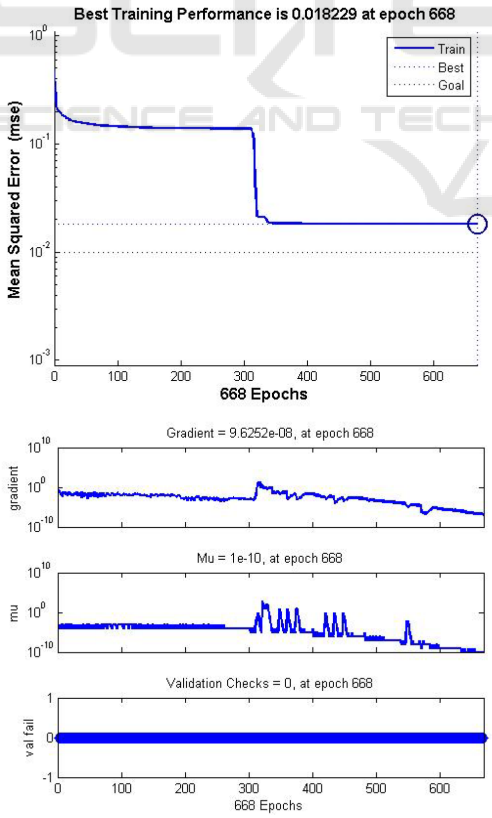

Figure 3: Neural network training performance.

Next, we test the trained network and select 5 sets of data as the test input data. The test code is $Y = sim(net, Ptest)$. The test data is shown in Table 6. According to the European norm theory, the error of the test result is very small. It can be determined that the network meets the requirements of air traffic safety assessment after training.

5 CONCLUSION

Based on the indicator system of security risk assessment of air traffic control, use the rough set theory to reduce the influencing factors. It can reduce the input attributes from 24 to 13, remove the redundant attributes and simplify the complexity of the network structure. Improve network training rate, and get training results more quickly and accurately. Design a complete BP neural network, build a learning model, and excavate the potential relationship within the data. It can be seen from the test samples that the constructed network can meet the requirements of air traffic control security risk assessment, and provide the forecast risk assessment level objectively and accurately. It is in favour of the practical work of the ATC.

REFERENCES

Al Basman, M.& Hu, J. 2012, Approaches for stochastic safety analysis arising in ATM application. *Decision and Control. IEEE*, 2012:514-519.

Bruin, T D, Verbert, K.& Babuška, R. 2017， Railway Track Circuit Fault Diagnosis Using Recurrent Neural Networks. *IEEE Transactions on Neural Networks & Learning Systems*, 2017, 28(3):523.

Cruck, E.& Lygeros, J. 2015, Hybrid modeling for the evaluation of risk perception by air-traffic controllers. *Control Conference. IEEE*, 2015:1278-1283.

Du H, Li H.& Yuan L. 2010, Risk assessment model for air traffic control based on fuzzy-ANP method. *China Safety Science Journal*, 2010, 20(12):79-85. (in Chinese)

Ge Z.& Sun Z. 2007, *Neural Network Theory and Realization of MATLAB R2007* . Publishing House of Electronics Industry, 2007

Guo J, Li Y.& Yang C. 2016, Classfication for general aviation air traffic management operation security based on gray analytic hierarchy process method. *Safety and Environmental Engineering*, 2016, 23(2):162-166. (in Chinese)

Liao Y, Guo J.& Yang C. 2015, Probability assessment of ATM safety based on bayes analysis. *China Science Paper*, 2015(19):2271-2275. (in Chinese)

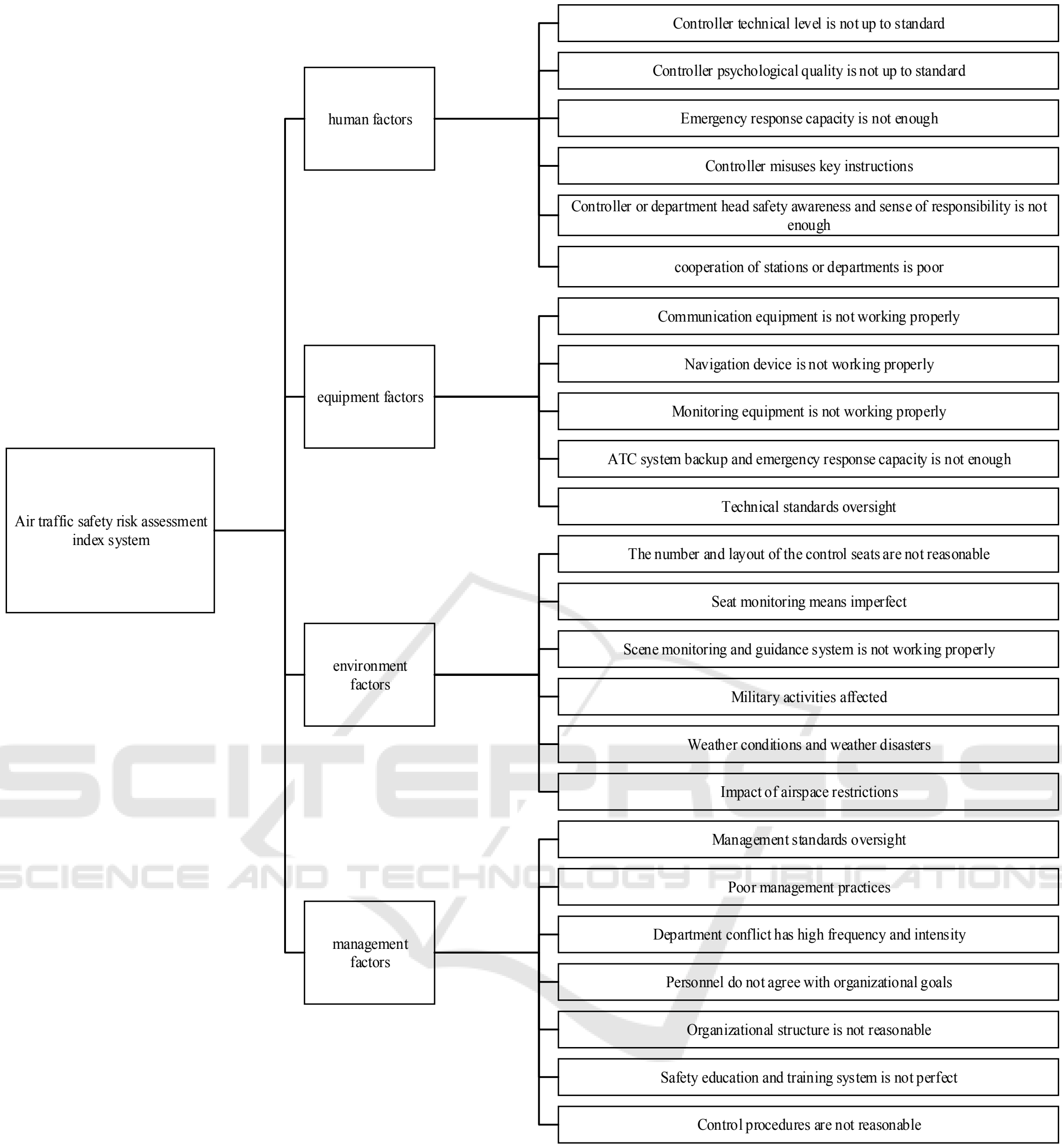

Figure 4: Air traffic safety risk assessment index system.

Table 6: Test data.

U	X1	X2	X3	⋯	X20	X23	output value					expected value	assessment level
U1	1	1	3	⋯	3	1	0.11621	0.01528	0.82108	0.08179	0.00001	0 0 1 0 0	3
U2	3	1	3	⋯	1	1	0.01702	0.89169	0.11587	0.00964	0.00051	0 1 0 0 0	2
U3	3	3	1	⋯	3	1	0.04513	0.00079	0.99243	0.00050	0.00242	0 0 1 0 0	3
U4	1	2	2	⋯	2	3	0.17850	0.80827	0.00123	0.01184	0.00706	0 1 0 0 0	2
U5	2	1	2	⋯	2	1	0.88620	0.00984	0.16700	0.00888	0.00096	1 0 0 0 0	1

Liu W, Wang P.& Sun D. 2010， Forecasting model of road traffic accident based on improved BP neural network. *Computer Systems and Applications*, 2010, 19(10):177-181.

Lu W. 2017, Talking about the concept of safety management system and popularization in civil aviation. *China High Tech Enterprises*, 2017(8):234-235. (in Chinese)

Luo F, Jia G.& Chen G. 2009, Design and optimization of index system for the ATC safety risk management. *China Safety Science Journal*, 2009, 19(8):115-120. (in Chinese)

Ma L.& Chang Y. 2017, Highway construction investment risk evaluation using BP neural network model. *International Conference on Industrial Technology and Management. IEEE*, 2017:154-158.

Shyur, H J. 2008, A quantitative model for aviation safety risk assessment. *Computers & Industrial Engineering*, 2008, 54(1):34-44.

Silva, T V D, Monteiro, R V A.& Moura, F A M. et al. 2017, Performance Analysis of Neural Network Training Algorithms and Support Vector Machine for Power Generation Forecast of Photovoltaic Panel. *IEEE Latin America Transactions*, 2017, 15(6):1091-1100.

Wang X. 2013, Several rough models and the combination of rough set and neural network research. *University of Electronic Science and Technology of China*, 2013. (in Chinese)

Wang G, Hu J.& Zhang Q, et al. 2011, Granular computing based data mining in the views of rough set and fuzzy set. *IEEE International Conference on Granular Computing. IEEE*, 2011:67-67.

Zhang X, Han S.& Yang C. 2016, An fuzzy synthetic evaluation model for safety risk in air traffic control based on matter element analysis . *Journal of transport information and Safety*. 2016, 34(4):50-56. (in Chinese)

Zellweger, A G.& Donohue, G L. 2015, Accident Risk Assessment for Advanced Air Traffic Management. *Minerva Chirurgica*, 2015, 14(4):214-5.