Risk Index Prediction of Civil Aviation Based on Deep Neural Network

NI Xiaomei, *WANG Huawei*[*], *CHE Changchang*

College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, P. R. China

(Received 9 September 2017; revised 8 April 2019; accepted 8 April 2019)

Abstract: Safety is the foundation of sustainable development in civil aviation. Although catastrophic accidents are rare, indicators of potential incidents and unsafe events frequently materialize. Therefore, a history of unsafe data are considered in predicting safety risks. A deep learning method is adopted for extracting reactions in safety risks. The deep neural network (DNN) model for safety risk prediction is shown to extract complex data characteristics better than a shallow network model. Using extended unsafe data and monthly risk indices, hidden layers and iterations are determined. The effectiveness of DNN is also revealed in comparison with the traditional neural network. Through early risk detection using the method in the paper, airlines and the government can mitigate potential risk and take proactive measures to improve civil aviation safety.

Key words: unsafe events; risk index; neural network; denoising auto encoder

CLC number: V328 **Document code**: A **Article ID**: 1005-1120(2019)02-0313-07

0 Introduction

Safety risks in civil aviation are related to several areas, such as flight safety, equipment failure, human factors, and bad weather conditions. Risks are associated with accidents and losses[1]. The randomness and probability of risk bring the uncertainty and increase the difficulty of safety risks detection.

This study focuses on analyzing risk levels based on deep learning. Risk levels in the civil aviation can be measured by the risk index. According to the reports from the Civil Aviation Administration of China (CAAC), most predictions are based on historical data by establishing the model and analyzing the data. Searching for a latent regularity from complicated data is a challenge. Moreover, the model for large aircraft data presents another difficulty.

In recent decades, the focus of aviation safety management is to prevent aviation accidents and reduce by the prevailing methods. Several methods that consider risk factors comprehensively, have been put forward such as fault trees, decision trees, probabilistic risk assessment (PRA), and fuzzy comprehensive evaluation (FCE). Moreover, application of various networks has introduced new approaches to aviation risk analysis, such as neural network (NN) and Bayesian neural network (BNN)[2]. Furthermore, the roles of the network have become crucial with the development of science and technology.

Li et al.[3] brought forward a new idea that the Markov theory was used twice, where the first time is to extend the original data and the second to calculate and estimate the residual errors. Then by comparing the original data sequence from a fault prediction case with the simulation sequence produced by the use of GM(1.1) and the new GM method, results conform to the original data. Taking Guangzhou city as an example, Liu et al.[4] applied the risk index assessment model for assessing the risk of each region and found that it is in line with the reality of urban accident disaster risk. Yang et al.[5] combined the genetic algorithm and the NN to compute the risk index of vessel's collision by multiple pa-

*Corresponding author, E-mail address: wang_hw66@163.com.

How to cite this article: NI Xiaomei, WANG Huawei, CHE Changchang. Risk Index Prediction of Civil Aviation Based on Deep Neural Network[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2019,36(2):313-319.
http://dx.doi.org/10.16356/j.1005-1120.2019.02.014

rameters. Moreover, aviation Brooker[6] examined the ability of BBN-based techniques to make accurate aviation risk predictions.

The characteristics of aviation safety risk can be summarized as follows. First, substantial sample data is needed to predict aviation safety risk. Second, shallow learning is used as a primary model in aviation safety risk prediction, for example BNN, support vector machine, and maximum entropy methods. These shallow learning methods contain one or no hidden layer. It is difficult to analyze aviation safety risk by these models. Moreover, the sample features are simplified through experience and technique.

Aviation safety analysis is one of the most popular topics in air transportation. Research on aviation safety assessment and prediction is significant in improving aviation safety in the future. The increasing amount of researches pay more attention to comprehensive assessment and prediction rather than simple prediction. Recent researches on aviation safety have demonstrated that most shallow learning methods can overcome insufficient sample size and fitting problem. However, these methods are insufficient in dealing with nonlinear data and residual errors.

Potential risks can lead to a series of unsafe events or accidents. Therefore, it can affect aviation safety risk level. In this paper, unsafe event data have been used to expand data size due to the few typical sample characteristics of aviation accident data. The data also reflects the characteristics of aviation risk. In recent years, deep learning methods have been widely applied to the classification and prediction problem research. Deep neural network (DNN) features more than one hidden layer of activation functions[7] and has been used to predict risk. DNN has broad application value for improving aviation operation management and preventing accidents from occurring.

In this paper, the civil aviation safety data system is firstly introduced. Then the deep learning model of the prediction is shown. Finally, the proposed DNN approach for risk prediction with unsafe events is described and made comparison with NN.

1 Civil Aviation Safety Data System

1.1 Risk evaluation index

Risks can be described by consequence and frequency. According to the Safety Management Manual (SMM) of International Civil Aviation Organization (ICAO)[8], risks can be categorized within a risk assessment matrix. Table 1 presents the severity of consequence categories and Table 2 provides the likelihood of occurrences. In Table 1, the more serious accident, the higher t value. Similarly, the more accidents that occur, the higher value. Otherwise, the lower the value.

In general, catastrophes rarely occur. In fact, there are no catastrophes in China since August 24, 2010. Incidents and unsafe events with slight influence on safety usually occur. However, incidents and unsafe events will result in accidents if potential risks are triggered and accumulated.

Table 1 Severity of consequences

Severity	Meaning	Value
Catastrophic	Equipment destroyed	5
Hazardous	A large reduction in safety margins, physical distress or a workload such that the operators cannot be relied upon to perform their tasks accurately or completely; Serious injury or death to a number of people; Major equipment damage	4
Major	A significant reduction in safety margins; a reduction in the ability of the operators to cope with adverse operating conditions as a result of an increase in workload, or as a result of conditions impairing their efficiency. Serious incident; Injury to persons	3
Minor	Nuisance. Operating limitations; Use of emergency procedures; Minor incident	2
Negligible	Little consequence	1

Table 2 Likelihood of occurrences

Qualitative definition	Meaning	Value
Frequent	Likely to occur many times	5
Occasional	Likely to occur sometimes	4
Remote	Unlikely, but possible to occur	3
Improbable	Very unlikely to occur	2
Extremely improbable	Almost inconceivable that the event will occur	1

1.2 Unsafe events of civil aviation

Compared with visible risks, more potential risks have not been detected and extracted. Nonetheless, the root cause of the risks remains, which can be stimulated or triggered in certain conditions or external environments. Potential risks of civil aviation safety should be recognized and detected. Therefore, risk detection is more important than risk evaluation to meet the demands of civil aviation safety management. In addition, if potential danger is discovered early, effective actions can be taken earlier. Avoiding accidents by taking actions before their occurrence is meaningful.

According to statistical analysis reports of unsafe events, unsafe incidents are divided into six categories from the point of view of accidents' types: Flight crew, aircraft maintenance, air traffic control, ground support, weather, and mechanics failure. Risk indices are calculated by the reports from January 2012 to May 2016 (see Table 3). Fig.1 illustrates the changing laws of the risk indices and indicates that it is difficult to find the potential law

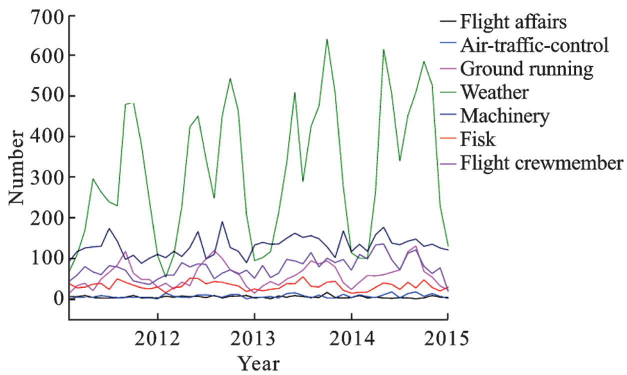

Fig.1 Initial data of six categories of unsafe events and risk indices for four years

with unsafe events.

The reasons can be summarized as follows. First, the civil aviation safety system is a typical complex large system, and its component elements interact with each other. The system condition is nonlinear. Thus, it is difficult to extract a significant linear expression between the influential factors and risk indices. Second, the interactions of influential factors make the randomness and uncertainty apparent in the civil aviation safety system. Therefore, accident occurrences are random and unpredictable. Third, an accident chain from hidden dangers to the occurrence of accidents is created. A high level of uncertainty can be demonstrated by risk accumulation and spread. Therefore, accident occurrences are random and unpredictable.

Table 3 Risk indices for civil aviation of China from 2012 to 2016

Month	Year				
	2012	2013	2014	2015	2016
1	36.9	14.9	19.5	15.6	21.4
2	27.0	27.4	23.4	16.6	15.6
3	28.4	29.7	25.3	28.2	27.4
4	35.6	50.8	36.9	38.5	45.1
5	37.6	49.6	36.4	38.2	35.5
6	23.2	36.6	54.0	23.2	
7	49.1	41.9	30.3	40.5	
8	40.2	40.2	29.1	26.3	
9	33.0	35.2	41.0	46.3	
10	26.8	31.5	42.7	27.7	
11	24.1	18.1	20.7	19.0	
12	29.1	24.4	14.2	29.1	

1.3 Methods of risk prediction of aviation safety

From the above reasons, risk prediction can not be fulfilled by samples using traditional risk prediction methods. Compared with shallow learning, the deep learning model is an artificial NN with multi-hidden layers, which models the network by unsupervised learning. The deep learning model includes the deep belief network (DBN) and the convolutional neural network (CNN), which perform well on feature extraction and sample classification. The deep learning method is suitable for the study of potential risks with various complicated factors because of its flexibility and compatibility. In this paper, the deep neural network (DNN) is used to build the deep network.

2 Risk of Civil Aviation Prediction Model

2.1 DNN structure and learning mechanism

DNN is a hybrid model with deep and proved structure that combines traditional multi-layer perception and recently developed pre-training technologies. Unsupervised pre-training is conducted for one layer. If all layers have been pre-trained, the parameters are used for initialization of network optimization, with respect to the supervised training criterion, or a logistic regression layer can be directly added on top of the network.

2.1.1 Auto-encoder(AE)

AE[9] is a type of unsupervised feature learning algorithm to make high dimensional input equal to the high dimensional output by encoding and decoding networks. AE is the feature representation for input data.

(1) Encoding process

The mapping function between the input layer and the hidden layer can be defined as

$$\boldsymbol{y}=f_\theta(\boldsymbol{x})=s(\boldsymbol{W}\boldsymbol{x}+\boldsymbol{b}) \tag{1}$$

where $s(\cdot)$ is the encoder activation function, $\boldsymbol{\theta}$ the encoding parameters and $\boldsymbol{\theta}=\{\boldsymbol{W},\boldsymbol{b}\}$. $\boldsymbol{W}$ is a weight matrix and $\boldsymbol{b}$ a bias vector. $\boldsymbol{y}$ is the other representation for $\boldsymbol{x}$, which is the encoding process.

(2) Decoding process

$\boldsymbol{z}$ is the reconfiguration from $\boldsymbol{y}$, which is the decoding process. The mapping function can be described as

$$\boldsymbol{z}=f_{\theta'}(\boldsymbol{y})=s'(\boldsymbol{W}'\boldsymbol{y}+\boldsymbol{b}') \tag{2}$$

where $s'(\cdot)$ is the decoder activation function, $\boldsymbol{\theta}'$ the decoding parameter and $\boldsymbol{\theta}'=\{\boldsymbol{W},\boldsymbol{b}\}$. $\boldsymbol{W}'$ is a weight matrix and $\boldsymbol{b}'$ a bias vector. $\boldsymbol{y}$ is the other representation for $\boldsymbol{x}$, which is the encoding process.

When the loss function is small, features learned from input data are large. The loss function can be described as

$$L(\boldsymbol{x},\boldsymbol{z})=H(B_x|B_z)= -\sum_{i=1}^{n}\sum_{k=1}^{d}\begin{bmatrix}\boldsymbol{x}_i[k]\lg\boldsymbol{z}_i[k]+\\(1-\boldsymbol{x}_i[k])\lg(1-\boldsymbol{z}_i[k])\end{bmatrix} \tag{3}$$

where $\boldsymbol{x}_i[k]$ denotes the k-th component of $\boldsymbol{x}_i$ and $\boldsymbol{z}_i[k]$ is the corresponding reconstructed value.

$$\boldsymbol{\theta}^*,\boldsymbol{\theta}'^*=\operatorname{argmin}\frac{1}{n}\sum_{i=1}^{n}L(\boldsymbol{x}_i,\boldsymbol{z}_i)= \operatorname{argmin}\frac{1}{n}\sum_{i=1}^{n}L(\boldsymbol{x}_i,g_{\theta'}(f_\theta(\boldsymbol{x}_i))) \tag{4}$$

where $\boldsymbol{\theta}^*$ and $\boldsymbol{\theta}'^*$ are the optimal parameters.

2.1.2 Denoising auto-encoder (DAE)

In the model, DAE[10] is used instead of AE. The noise variables are added for DAE. The input $\boldsymbol{x}$ is replaced by $\hat{\boldsymbol{x}}$ containing noise. The stochastic mapping can be described as $\hat{\boldsymbol{x}}\sim q_D(\hat{\boldsymbol{x}}|\boldsymbol{x})$.$q_D$ is a process of noise adding[11]. In this case, the Gaussian noise for $\boldsymbol{x}$ is chosen. In this work, the unsafe events are used as input data, which are independent identically distributed (i.i.d). Samples from an unknown distribution after pre-processing.

In DAE model, Eq.(1) can be described as

$$\boldsymbol{y}=f_\theta(\boldsymbol{x})=s(\boldsymbol{W}\hat{\boldsymbol{x}}+\boldsymbol{b}) \tag{5}$$

The loss function can be described as

$$\boldsymbol{\theta}^*,\boldsymbol{\theta}'^*=\operatorname{argmin}\frac{1}{n}\sum_{i=1}^{n}L(\boldsymbol{x}_i,\boldsymbol{z}_i)= \operatorname{argmin}\frac{1}{n}\sum_{i=1}^{n}L(\boldsymbol{x}_i,g_{\theta'}(f_\theta(\hat{\boldsymbol{x}}_i))) \tag{6}$$

By setting the latent representation (encoded output) of DAE found on the layer below as the input to the current layer, DAE can be stacked to form a deep network[12]. Fig.2 shows the structure of DNN. The advantages of DAE in this model can be summarized as follows.

(1) DAE has a deep structure for better learn-

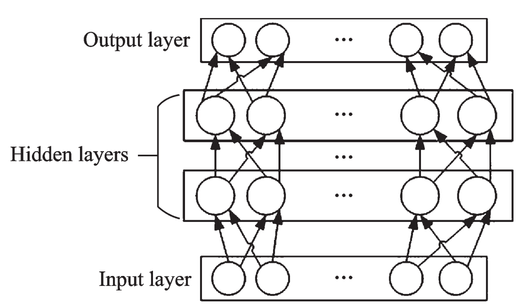

Fig.2 Structure of DNN

ing of data characteristics, which avoids poor generalization ability of traditional shallow structure algorithm.

(2) DAE can fuse information from various sources on risk of civil aviation, which can take full account of the correlation between the information and avoid the phenomenon of information overlap.

(3) DAE adopts greedy training layer by layer, which solves the training problem of traditional neural networks and avoids the local minimum.

(4) DAE can effectively reduce the overfitting compared with the traditional neural networks.

2.2 Steps of prediction model

The steps of risk prediction on civil aviation are shown in Fig.3.

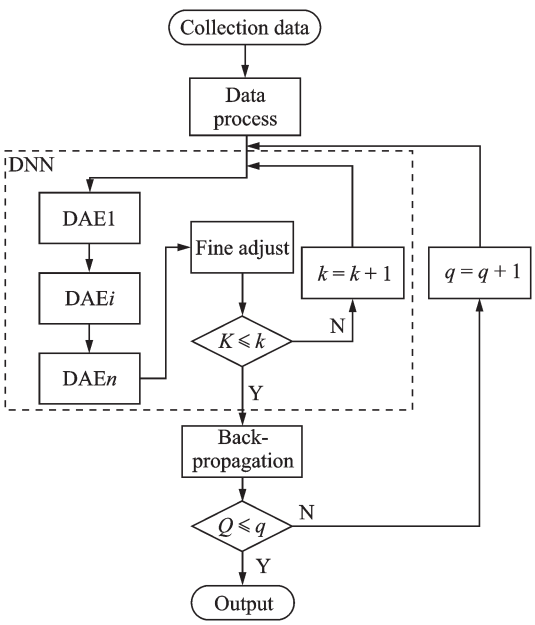

Fig.3 Steps of risk prediction in civil aviation

Step 1 To ensure that the data is collected and meets the demand $\boldsymbol{x} \in [0,1]^d$ mentioned above, the six kinds of unsafe events are normalized.

Step 2 The DAE is stacked to form DNN under the training. The input data of unsafe events is trained to extra features by being encoded and decoded.

Step 3 DNN with BP neutral network is back-tuned when the iterative times k meets the setting value K.

Step 4 Back-tuning in Step 3 is repeated until the iterative times q of the entire network meet the setting value Q. The mean squared error (MSE) is calculated to judge the accuracy.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(y_{\text{prediction}} - y_{\text{initial}})^2}{n} \tag{7}$$

where $y_{\text{prediction}}$ denotes the predicted data, and y_{initial} the initial data.

3 Example

The data of unsafe events collected from 2012 to 2015 are used as training samples. The data from January to May in 2016 are adopted as test samples. All data verify the effectiveness of the proposed algorithm.

3.1 Data processing

The data obtained from a range of four years is too small. This least square method here is used to fit the points which are drawn by the initial data and the pre-disposal data. The pre-disposal data presented in Table 4 is the moving average of the same month from the different years. Six variables, including flight crew (x_1), aircraft maintenance (x_2), air traffic control (x_3), ground support (x_4), weather (x_5) and mechanics failure (x_6), and risk index y are presented. Every figure is sampled to get 1 620 sets of data as the training data. The initial and pre-disposal data are denoted as the testing data to train this network. Then, the data set is extended as 6 (variables) × 1 800 (training data), which is 10 times bigger than the initial and pre-disposal data.

Table 4 Data set descriptions

Data type	Usage	Data set
Initial data	Train the network	4(year) × 12(month) × 6(variable)
Pre-disposal data	Develop the initial data	11(group) × 12(month) × 6(variable)
Fitting data	Develop the training data	1 620(point) × 6(variable)
Test data	Test the network	5(month) × 6(variable)

3.2 Risk prediction of civil aviation safety

Effectiveness of the network is proven by MSE (Eq.(7)) with different iterations and layer numbers. The three kinds of hidden layers with the same iterations are shown in Table 4. The best structure of hidden layers with different iterations is tested (see Table 5).

Table 5 MSE of DNN with different layer numbers

Group	Round 1	Round 2	Round 3
Layer number	10-8-5	6-6-6	6-4-2
MSE	0.105	0.227	0.418

Table 6 presents the MSE with different iterations of DNN, indicating that the MSE is small when the iteration time reaches 6 000. After comparing with the three groups, the result is obvious. The first round is considered as the most effective among the three predictions. The hidden layer is 10, 8, and 4, and the iteration is 6 000.

Table 6 MSE of DNN with different iteration time

Group	Round 1	Round 2	Round 3
Iteration time	6 000	8 000	4 000
MSE	0.105	0.316	0.418

The network is trained with the six variables as the input data and the initial risk indices of five months as the target data. The input layer is formed by the training data, and the first hidden layer is obtained with DAE. The data are inputted in the hidden layer similar to the input layer, and the next hidden layer is obtained. The data from the hidden layer is also the input data of the next layer[13]. The process is vividly shown in Fig.2. In this study, three hidden layers are sufficient to derive the effective network after several tests.

Fig.4 shows the risk prediction of civil aviation safety from January to May 2016. The output is floating in an acceptable range, as shown in Table 3. The real risk indices and prediction errors are given in Table 7. From the results, it is seen that the six aspects are suitable for predicting risk index. Concurrently, the prediction of risk index also provides reference for safety management and decision.

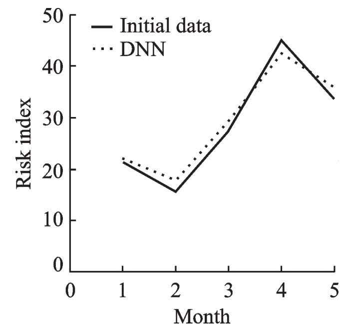

Fig.4 Prediction data of DNN and initial data

Table 7 Risk indices and prediction errors of DNN

Month	Initial data	DNN	Error/%
1	21.4	22.1	3.27
2	15.6	17.8	14.1
3	27.4	29.8	6.9
4	45.1	42.5	−5.76
5	33.5	35.8	9.85

3.3 Comparison

NN shows obvious advantages on fitting the nonlinear problem[14]. For risk prediction of civil aviation safety, traditional NN is used to compare with DNN. Tables 7 and 8 provide the risk prediction results comparison of different methods. Fig. 5 illustrates the predictions comparison of risk indices with NN and DNN. Tables 7, 8 and Fig. 5 show that DNN prediction accuracy is better than that of NN.

In traditional NN, training is easy to trap in local optimum as the network weights for this network because of the complexity of the error function. In

Table 8 Risk indices and prediction errors of NN

Month	Initial data	NN	Error/%
1	21.4	24.6	15
2	15.6	22.2	42.3
3	27.4	29.7	8.4
4	45.1	35.2	−21.95
5	33.5	33.5	0

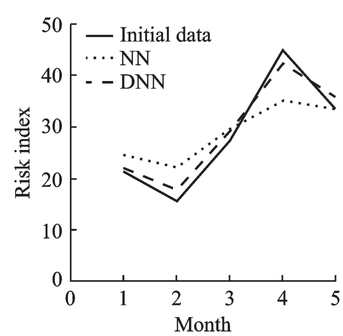

Fig.5 Prediction data of DNN and NN and initial data

addition, the great fluctuation of the prediction error indicates the instability of the traditional neural networks. Moreover, the Mse according to Eq.(7) is 1.6, which is larger than the error of DNN.

4 Conclusions

By analyzing five years of unsafe events data including flight crew, aircraft maintenance, air traffic control, ground support, weather and mechanics failure, a risk index prediction model to evaluate the safety of civil aviation using DNN is developed in this paper. The DNN is obtained by stacking DAEs. The data of unsafe events collected from 2012 to 2015 is extended as the training parameters and unsafe events in 2016 are the testing parameters. This study demonstrates the effectiveness of proposed method compared with traditional NN in accuracy and stability. Moreover, with the development of civil aviation, once the amount of data is large enough, it can be directly predicted by the DNN without expanding the data, which can learn the features and information more deeply than the traditional ones.

References

[1] JANIC M. An assessment of risk and safety in civil aviation[J]. Journal of Air Transport Management, 2000, 6(1): 43-50.

[2] WANG H W, WU H Q. Reliability evaluation model based on data fusion for aircraft engines[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2012,29(4): 318-324.

[3] LI Y P, JIA C L. Partial improvement of traditional grey-Markov model and its application on fault prediction[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2017,34(4): 449-455.

[4] LIU G, WU Z Z, LI S Y. Study on risk index assessment method of urban accident disasters [C]// International Conference on Reliability. Guangzhou, China: IEEE Maintainability and Safety, 2014: 1119-1123.

[5] YANG G P, YANG Z X. Research of computing the vessels' collision risk index by multiple parameters based on neural network with genetic algorithm [C]// International Conference on Instrumentation. Shenyang, China: IEEE, 2013: 712-714.

[6] BROOKER P. Experts, Bayesian belief networks, rare events and aviation risk estimates[J]. Safety Science, 2011, 49(8): 1142-1155.

[7] DALTO M, MATUSKO J, VASAK M. Deep neural networks for ultra-short-term wind forecasting [C]//IEEE International Conference on Industrial Technology. Seville, Spain: IEEE, 2015: 1657-1663.

[8] ANDREI F. ICAO Doc 9859 AN/474, Safety management manual[S]. USA: [s.n.], 2011, 3(1): 129-130.

[9] BENGIO Y, LAMBLIN P, POPOVIEI D, et al. Greedy layer wise training of deep networks [C]// Proc of the 12th Annual Conference on Neural Information Processing System. Canada: MIT Press Cambridge, 2006: 153-160.

[10] CHEN Z, DENG S, CHEN X, et al. Deep neural networks-based rolling bearing fault diagnosis [J]. Microelectronics Reliability, 2017, 3(6): 327-333.

[11] VINCENT P, LAROCHELLE H, BENGIO Y, et al. Extracting and composing robust features with denoising auto-encoders [C]//International Conference on Machine Learning. New York, USA: ACM, 2008: 1096-1103.

[12] HU Q, ZHANG R, ZHOU Y. Transfer learning for short-term wind speed prediction with deep neural networks[J]. Renewable Energy, 2016, 85: 83-95. (in Chinese)

[13] BENGIO Y. Learning deep architectures for AI [J]. Foundations and Trends in Machine Learning, 2009, 2: 1-127.

[14] CHEN G. Analysis of influence factors for forecasting precision of artificial neural network model and its optimizing [J]. Pattern Recognition & Artificial Intelligence, 2005, 18(5): 528-534. (in Chinese)

Acknowledgement This work was supported by the Joint Funds of the National Natural Science Foundation of China (No. U1833110).

Authors Ms. **NI Xiaomei** is a Ph.D. candidate at College of Civil Aviation, Nanjing University of Aeronautics and Astronautics(NUAA). Her research focuses on the risk control and management.

Prof. **WANG Huawei** is a doctoral supervisor at College of Civil Aviation, NUAA. Her main research areas are civil aviation safety engineering, reliability engineering and vehicle operation engineering.

Mr. **CHE Changchang** is a Ph.D. candidate at College of Civil Aviation, NUAA. His research focuses on the vehicle operation engineering.

Author contributions Ms. **NI Xiaomei** designed the study, complied the models, conducted the analysis, interpreted the results and wrote the manuscript. Prof. **WANG Huawei** contributed to the discussion and background of the study. Mr. **CHE Changchang** contributed data and model components for the risk index prediction model. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

(Production Editor: Wang Jing)