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Research on Risk Early-Warning Model in Airport Flight Area based on Information Entropy Attribute Reduction and BP Neural Network

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Abstract

According to the fussy of evaluating index and the uncertainty of evaluating information in flight area, systems thinking tool of complex science management theory - explore graph, is used to construct the fight area risk evaluation index system. And a fight area risk early-warning model based on information entropy attribute reduction and multi-layer BP neural network is proposed. First rough set and information entropy are combined, based on information entropy attribute reduction algorithm, the reduced index information are got. Then based on the multi-layer BP network, the data collected from the flight area was intelligent reasoned and analyzed and evaluated. An example analysis by MATLAB shows that the method is feasible, and it provides support for venture investment project risk management evaluation method.

Keywords: *Exploring Graph, Flight Area, Risk Early-Warning, Information Entropy, BP Network*

1. Introduction

At present, Chinese aviation entered a phase of rapid development, air transport maintain an average annual growth rate of more than 10%, however due to various reasons, it is difficult to avoid the occurrence of accidents of the civil aviation airport. Therefore, if we can supervise some personnel, equipment, environment and management problems in the flight area, improve airport flight area emergency rescue facilities, establish the early warning organization and perfect the emergency management system, many accidents can be avoid. PinYun, etc.[1] made a special study in the civil aviation airport security early warning management organization, and put forward the corresponding early warning index and fuzzy evaluation model. LiHang, etc [2] used the extension dynamic evaluation model based on variable matter element theory, and then constructed the airport security early warning model. Christina Neal, Olga Girina [3] used security MS model of social technology system constructed the aviation safety early warning system. Ginati A &Coppola A.D [4] studied the birds of the aviation disaster risk prevention, put forward poses serious problems for aviation safety bird strike risk early warning model. Zhao gui-hong, etc. apply the artificial neural network to the apron safety management, they use factor analysis to extract the common factors, and use artificial neural network to train and make prediction of apron safety, finally get the safety condition of apron [5]. YangYu and other scholars analyze factor according to the safety risk status of civil airport, construct a hierarchical structure system, and establish a model to evaluate the airport security risk by using the method of analytic hierarchy

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process and grey system theory, which illustrated the method's practicality and maneuverability by numerical examples [6]. At present the research of security early warning simulation of flight area model is still lacking [7-9]. Using the theory of complexity science management, combined with the attribute reduction of rough set and multilayer BP neural network to build early warning models of the security risk of flight area is rare.

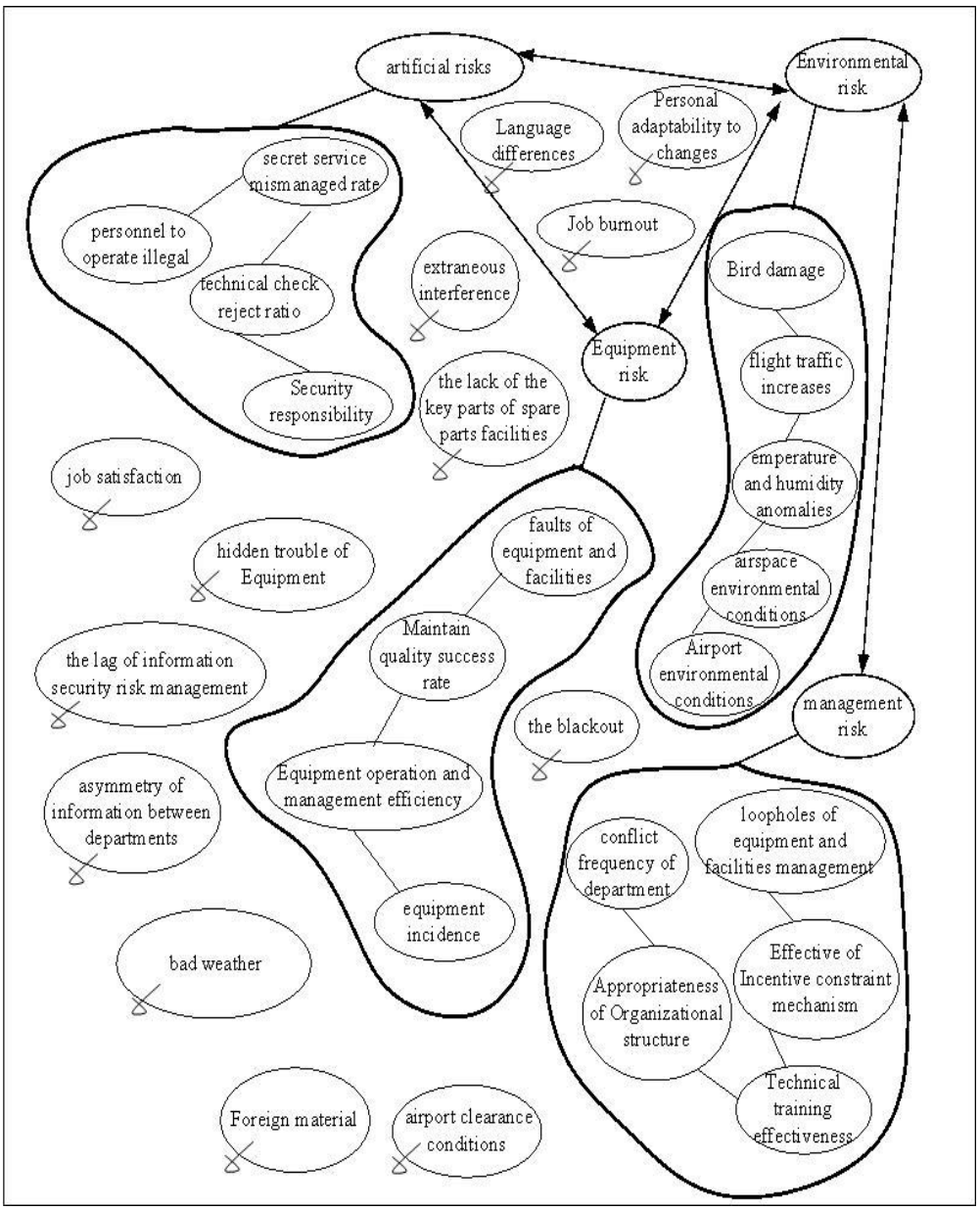

Figure 1. Classified Exploring Graph of Airport Airfield Security Risk Early Warning

In view of this, a exploring graph tool [10-11] in complex scientific management theory is used to build a airfield security risk warning index system, and a risk assessment model based on information entropy attribute reduction and multi-BP neural network is proposed. First the impact indicators, which are extracted from numerous risk factors airfield safety key by attribute reduction algorithm based on information entropy [12-13], are used as the input layer of the neural network to

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reduce the design complexity of neural networks and computational complexity; Then the collected training data of security risks are classified into training, validation and testing to approach Boolean vector. As a result, the network, which has associative memory and ability to predict, can identify nonlinear relationship between input and output, then provide new ideas and methods to achieve flight area intelligent reasoning and forecast for airports flight safety risk warning.

2. Risk Early-Warning Index System in Airport Flight Area based on Exploring Graph

Exploring Graph is a creation based on the researchers' experience, knowledge, information and the creation of imagination after investigating the overall environment via complex scientific management system. The formation of the figure is a collective creative process, showing all the factors that affect or may affect the research topic [10]. According to the steps of Exploring Graph, we get Classified Exploring Graph shown in Figure 1.

Based on above exploring graph, index system of Airport airfield security risk early warning is shown in Figure 2.

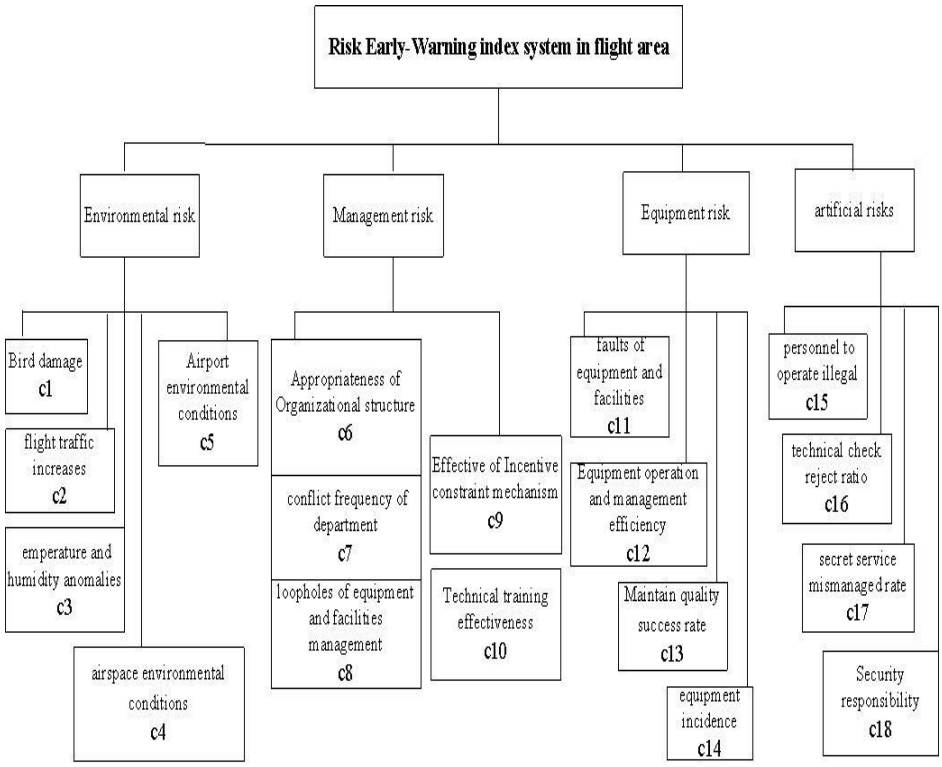

Figure 2. Risk Early-warning Index System in Flight Area

3. Risk Early-Warning Model in Airport Flight Area based on Information Entropy Attribute Reduction-BPNN

3.1 Attribute Reduction Algorithm based on Information Entropy

The attribute reduction is one of the important contents of rough set, which the main purpose is to remove the redundant or unimportant indexes and maintain the ability of classification index is unchanged in order to improve operation efficiency. The most widely used is based on attribute significance as heuristic information for

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the reduction algorithm. This paper introduces the theory of mutual information entropy, which considerate from the relative nuclear point of view, taking the mutual information as the heuristic information, combining the attribute of the conditional information entropy and the significance, setting the changes in the size of mutual information to a property caused by measure as the attribute importance, by sequentially adding importance of property until the formation of a maximum reduction.

$H(x) = -\sum_{i=1}^{n} p(x_i) \log p(x_i)$, it represent an attribute set entropy, the higher values indicate greater the uncertainty of the x; The conditional entropy of the attribute set y with respect to the x is $H(y \mid x) = -\sum_{i=1}^{n} p(x_i) \sum_{j=1}^{m} p(y_j / x_i) \log p(y_j / x_i)$, $i = 1, 2, ..., n, j = 1, 2, ..., m$.

Mutual information between y and X is: $I(y, x) = H(x) - H(x \mid y)$

Decision table $S = (U, A, V, f)$, $A = C \bigcup D$, $B \in C$, then the important degree of the any attributes is $SGF(b, B, D) = H(D \mid B) - H(D \mid B \bigcup \{b\})$. If $B = \varnothing$, then $SGF(b, B, D) = H(D) - H(D \mid \{b\})$ expresses that the mutual information between b and D, its value is bigger means b of D is more important.

The specific algorithm of attribute reduction based on information entropy is described below:

Input: decision table $S = (U, A, V, f)$

Output: relative reduction red

Process:

$red = \varnothing$;

$H(D) = -\sum_{i=1}^{n} p(D_i) \log p(D_i)$;

$I(C, D) = H(D) - H(D \mid C)$;

$core = \varnothing$;

FOR i=1 TO n //n is the number of condition attributes

BEGIN

$a = C[i]$

IF $f(x, D) != f(y, D)$ && $f(x, C - a) = f(y, C - a)$

$core = core \bigcup a$

END

$I(core, D) = H(D) - H(D \mid core)$

$a = (C - core)_{[1]}$

Max= $I(a, D)$

$R = core$

FOR j=2 TO m //m is the number of $C - core$

BEGIN

$a = (C - R)_{[j]}$

IF $I(a, D)$ >=Max THEN

BEGIN

Max= $I(a, D)$

$R = R \bigcup a$

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// Find properties to maximize the mutual information, add it to the reduction in the core

IF $I(R,D)=I(C,D)$ RETURN red=R

END

END

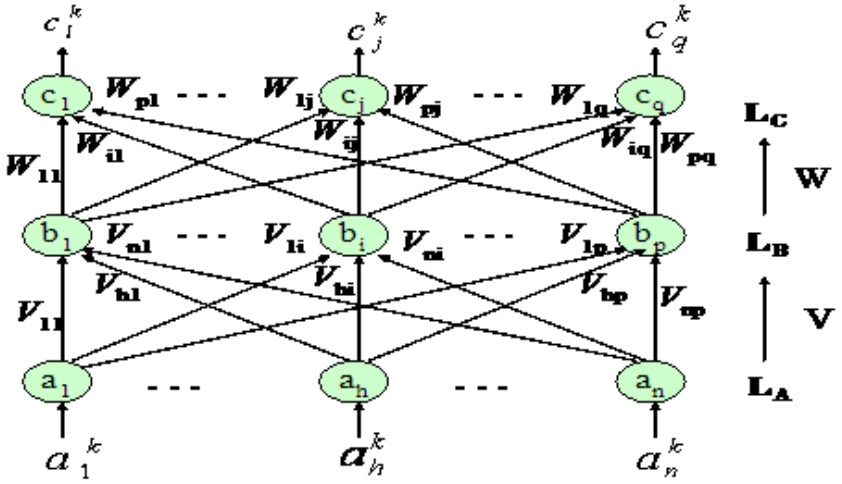

Figure 3. Basic Topology Structure of BP Network

3.2 Multi- BP Algorithm

The basic idea of BP algorithm [14-15] is as follows. Learning process involves two processes, including signal transmission and error back propagation. When it propagates forward, the input samples input from the input layer. After layer-by-layer processing by hidden layer, signal will be transmitted to the output layer. If the actual output of the output layer does not accord with the desired output, then transferred to the error back propagation stage. Error back propagation is to propagate back output error in some form through hidden layer to input layer, and the error is allocated to all units of each layer. Thus the error signal of each layer is obtained, which is the basis of correcting weights of each unit. Process of adjustment of each layer weights is carried out repeatedly. The process of continuous adjustment of weights is the network training process. This process will be carried out to a degree when the network output error is reduced to an acceptable level, and it will also stop training if it has achieved a pre-determined number of learning. The single hidden layer networks of BP network model are widely used, mainly including the input layer, hidden layer and output layer.

A basic topology structure of BP network is shown in Figure 3.

In the Three layer feed forward neural network, the input vector is $X=(x_1,x_2,\cdots,x_i,\cdots,x_n)^T$, like to join $x_0=-1$,can introduce a threshold for the hidden layer neurons; The output layer vector is $O=(o_1,o_2,\cdots,o_k,\cdots,o_r)^T$,the desired output vector is $d=(d_1,d_2,\cdots,d_k,\cdots,d_r)^T$, the input layer to the hidden layer weights matrix between the indicated by V, $V=(V_1,V_2,\cdots,V_j,\cdots,V_m)$,The column vector of V_j for the weight vector of hidden layer neurons corresponding to the first j ; hidden layer to output layer weights matrix between the indicated by W , $W=(W_1,W_2,\cdots,W_k,\cdots,W_r)$,The column vector of W_k for the weight vector of output layer neurons corresponding to the first k .The relationship between them is:

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$$O_k = f(net_k) \quad k = 1,2,\cdots,r$$

$$net_k = \sum_{j=0}^{m} w_{ik} y_j \qquad k = 1,2,\cdots,r$$

$$y_j = f(net_j) \qquad j = 1,2,\cdots,m$$

$$net_j = \sum_{i=0}^{n} v_{ij} x_i \qquad j = 1,2,\cdots,m$$

The transfer function is:

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

The above formula for mathematical model of three layer feed forward network.

BP learning algorithm for weight adjustment formula:

$$\Delta w_{jk} = \eta \delta_k^0 y_j = \eta (d_k - o_k) o_k (1 - o_k) y_j$$

$$\Delta v_{ij} = \eta (\sum_{k=0}^{r} \delta_k^0 w_{jk}) y_j (1 - y_j) x_i$$

Among them, $\eta \in (0,1)$, stands for the learning rate.

Establishing and network model with MATLAB [16] repeated training, in order to achieve the minimum error, can try to close to the actual value of pre side output. Specific steps are as follows:

(1) The data sample. The input vector is $X = (x_1, x_2, \cdots, x_i, \cdots, x_n)^T$, the output vector is $d = (d_1, d_2, \cdots, d_k, \cdots, d_r)^T$.

(2)The establishment of the network. The network name is *newff*(*PR*, *SN*, *TF*, *BTF*, *BLF*, *PF*), PR is [the input range], SN is [the number of neurons in each layer]. TF is [transfer functions of each layer], BTF is [network training function], BLF is the network weight threshold function, and PF is network performance function. The mean square error of the network output and the target output, it defaults to MSE.

(3) The parameter setting.

(4) Training network. The network name is train (network name, input variable name, the target variable name). This process is repeated to adjust weights and thresholds, so as to reduce the performance of the value function, until it reaches the preset precision error.

(5) Analog output. *SIM* (Network name, input variable name).

(6) To compare the sample observations and the fitting values. After the network training, the observed value and the fitted value comparison is the ability to predict the strength of test network. We have compared the number of parameters required in the process. The target accuracy, also known as network output and the target output mean square error. When the fitted values and target lines intersect, they should consider the goal line down, which improve the accuracy, and then training. The repeated adjustment of the parameters, so that the network is closer to the actual value.

3.3 Operation Process of Decision-making Model

In this study, effectiveness of the proposed model was demonstrated using an airport flight area in Wuhan as an example. Specific steps are as follows:

Step 1: According to the current index system to collect relevant data in this airport flight area.

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Step 2: Data is processed with the discrete way, then using the relative reduction algorithm processes and extracting major evaluation indicators.

Step 3: According to the extraction results, using the indicators normalized as the output neurons.

Step 4: Initializing parameters of BPNN and selecting evaluation samples, then using BPNN to train and learn it so as to establishing the model of Risk Early-Warning.

Step 5: At the end of the network training, compare the observed value and fitting value and analyze the performance.

4. Simulation Test

First of all, according to the demand of the airport airfield survey data and daily safety management data, the airport airfield security risk early warning degree is divided into 3 - without warning, 2 - mild early warning, 1 - moderate warning, 0-severe warning - a total of four grades. The actual data are collected based on above index system, which Includes 18 evaluations as Condition attributes. The risk early warning results ranks are used as the decision attributes, which marked as D. Discrete data samples are shown in table 1.

Table 1. Discrete Data Samples

ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
C1	2	2	3	3	2	2	3	2	2	2	3	3	2	2	3
C2	2	2	2	3	2	3	3	1	2	2	2	2	2	2	2
C3	1	1	1	1	1	1	1	1	2	2	2	3	2	3	3
C4	3	2	3	2	2	1	2	2	3	2	3	2	2	1	2
C5	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
C6	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
C7	3	2	3	4	2	1	3	2	2	2	2	2	2	2	2
C8	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
C9	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
C10	2	2	2	3	2	3	2	2	2	2	2	2	2	2	2
C11	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1
C12	1	1	1	1	1	1	1	1	3	2	3	4	2	1	3
C13	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
C14	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
C15	2	2	2	2	2	1	2	2	2	2	2	2	2	2	2
C16	3	3	2	3	2	2	3	2	2	2	2	3	2	2	1
C17	3	3	3	3	3	3	3	3	2	2	2	3	2	3	2
C18	3	3	4	2	3	1	2	3	1	1	1	1	2	1	1
D	1	1	2	1	0	0	2	1	3	2	0	1	2	3	2

Mixed model was adopted to treat with samples data. First of all, the attribute reduction algorithm based on information entropy described above was used to reduce the indicators; the reduction set $\{C2, C10, C12, C16, C18\}$ was got as the input layer of BP neural network. Security risk early warning degree is expressed by [0001] - no warning, [0010] - mild early warning, [0100] - moderate warning, [1000]-severe warning. A BP neural network was established with MATLAB. The network consists of three layers, and the input, hidden and output layers have 5, 4 and 4 neurons respectively. Simulation tests were carried out by using the top 11

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groups in sample data of the corresponding index of $\{C2, C10, C12, C16, C18\}$ as a BP neural network training data in Table 1, and the latter 4 groups as the test data. To comply with the logarithm of the S-function mapping range, the target will be normalized to the number of [0, 1]. After 36 steps training, network mean square error (MSE) has reached the requirement of standard 0.0001, as shown in figure 4. So far, the risk early-warning model in airport flight area has been constructed. In the future, other sample data can be calculated by this model only putting the normalization of the sample data input the model.

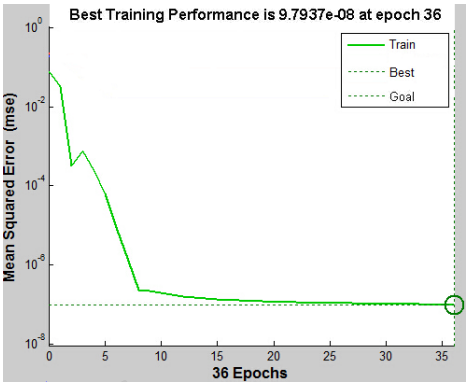

Figure 4. Training Process

The last 4 groups of sample data are tested as forecast samples, the predicted results are consistent with the measured ones. The results are shown in Table 2.

Table 2. Results of Predicted

Sample ID	Expectation of Output	Actual Output	Alert Degree
12	(0 1 0 0)	(0 1.0025 -0.02303 0)	moderate warning
13	(0 0 1 0)	(0 0 0.92618 0.12537)	mild early warning
14	(0 0 0 1)	(0.00246 0 0 1.00321)	No warning
15	(0 0 1 0)	(0 0 1.0165 -0.00774)	mild early warning

From Table 2, the results indicated that the output value of the error of the model and the true value are relatively small; the performance can meet the requirements of practical application.

5. Summary

Exploring graph tool is used to construct the airfield risk early-warning index system, by making full use of the wisdom of experts in this paper. Then rough set and information entropy are combined, the attribute reduction algorithm based on information entropy is proposed to reduce index, and on the basis of BP neural network, an airport flight area security risk early-warning model is constructed. The effectiveness of the proposed hybrid model is verified by MATLAB simulation, and it offers a new way of dynamic early warming of airport flight area security risk.

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