ANN RBF Based Approach of Risk Assessment for Aviation ATM Network

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Abstract: ATM (Asynchronous Transfer Mode) network is the core communication network of civil aviation aeronautical telecommunication network. So it is an urgent time to do scientific risk assessment for ATM network as soon as possible. According to threats and vulnerabilities existing in ATM network, which could bring bad influence to assets and missions of ATM network, even threaten the whole security situation of ATM network. This paper proposes risk assessment model based on RBF neural network. According to the established evaluation model, indexes that influencing the security situation of missions are used as input of the model and train the model. The well-trained neural network model is used to assess ATM network, while the results are compared to that of the traditional methods of scoring by experts for rounds of times. The experimental results demonstrate that the risk assessment model has strong capacities of self-learning and convergence, accords well with the complex ATM network for risk assessment. Copyright © 2013 IFSA.

Keywords: RBF neural network, ATM network, Risk assessment, MATLAB, Evaluation model.

1. Introduction

The civil aviation security is the backbone for aeronautical telecommunication network and greatly impacts on the national security of airspace, economy development and social stability. It is a significant research task for the defense strategy of national information security. Risk assessment is a series of processes to evaluate the level of risks an information system faced with by ascertaining the residuary risks in system and judging the level of risks whether acceptable or needs additional measurements to further reduce risks [1]. Risk assessment consists of three basic elements: scope and methods of assessment; collecting and analyzing data; demonstrating the results of risk analysis.

In this paper, the Delphi method is used to define ATM network risk assessment index system. Using 3-layer feed forward RBF neural network and local approximation theory, finding out the corresponding relationship between the process of risk assessment and modeling, using RBF network’s characteristics of fast learning and good nonlinear approximation ability, the paper makes the risk assessment model accurately for the complex relationships in ATM network risk assessment process in order to achieve the goal of getting objective scientific assessment results.

2. The Related Work

In civil aviation’s ATM (Asynchronous Transfer Mode) network, risks are man-made or natural threats and usually resulted from the vulnerabilities of ATM network telecommunication system,
physical environments and the missions, which may lead to the possibility of security incidents.

Artificial neural network (ANN) for the assessment of information security has been widely applied for the national key security systems and achieved a lot in the international community. During the risk assessment, the relationships of major targeted attributes are nonlinear and they are very difficult for general methods to reflect.

This paper extracts indexes from characteristics of civil aviation’s ATM network by using the Delphi method, and applies the indexes to practical risk assessment for civil aviation’s ATM network. These indexes data can be collected easily from the actual work. This paper establishes model of risk assessment based on radial basis function (RBF) artificial neural network, using MATLAB software to simulate, train and test the model, in the end, analysis the indexes in order to achieve the purpose in scientific and accurate way to do risk assessment for the ATM network.

3. Risk Assessment Model for ATM Networks Based on RBF Neural Network

3.1. Mission Model of Risk Assessment for ATM Network

Risk assessment on ATM network is considered from the following three aspects:

1) Asset, the value of ATM network and the things needed to protect, it exists in many forms, such as hardware, software, documents, etc.;

2) Vulnerability, the weak point of ATM network’s assets which could be threatened by threats, vulnerabilities can also be a hardware or software aspects;

3) Threat, the potential causes which could cause accidents to ATM network assets, it may come from inside or outside, such as destruction and electromagnetic leakage. According to these three aspects, this paper analyzes of the possible impact of ATM network’s mission because of the threats and vulnerabilities from the perspective of assets, and establishes 3-layer mission model of risk assessment, as shown in Fig. 1.

3.2. Indexes of ATM Network Risk Assessment

There is no generally accepted indicator system to establish an effective method. Delphi method [2-3] is one of the most widely used methods. In 1964, the U.S. Rand Corporation Helm and Gordon first systematically introduced how to use the Delphi method which synthesizes objective experience of most experts and subjective determinations with rounds of scoring by anonymous experts.

According to characteristics of potential threats and vulnerabilities of ATM network, this paper extracts indexes from following five aspects [4]: management security, physical and environment security, arrangement security, software and hardware security and air traffic management missions security.

Indexes, which constitute a network risk assessment indicator system, extracted by using Delphi method are shown in Table 1. ATM network security is the target layer (A). The first index layer (B) consists of five aspects such as management security, physical and environment security, arrangement safety, software and hardware security and air traffic management missions security. The second index layer (C) consists of 17 indexes, such as management regulations, safety training, anti-electromagnetic interference, anti-sabotage, power supply security, data classification, authentication center (CA), fault-tolerant backup, firewall, antivirus, IPS & IDS, operating system, application software, radar information, weather data, automatic switching segment, aeronautical information.

![Fig. 1. Assets, vulnerabilities and threats of ATM network.](image-url)
### Table 1. Risk assessment indicators system.

<table>
<thead>
<tr>
<th>Goal</th>
<th>Missions</th>
<th>Assets and Capacities</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATM network security (A)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Management Security (B1)</td>
<td>Management Regulations (C1)</td>
<td>Safety Training (C2)</td>
</tr>
<tr>
<td>Physical &amp; Environment Security (B2)</td>
<td>Anti-electromagnetic Interference (C3)</td>
<td>Anti-sabotage (C4)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Power Supply Security (C5)</td>
</tr>
<tr>
<td>Arrangement Security (B3)</td>
<td>Data Classification (C6)</td>
<td>Authentication Center (CA) (C7)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Fault-tolerant Backup (C8)</td>
</tr>
<tr>
<td>Software &amp; Hardware Security (B4)</td>
<td>Firewall (C9)</td>
<td>Antivirus (C10)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>IPS &amp; IDS (C11)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Operating System (C12)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Application Software (C13)</td>
</tr>
<tr>
<td>Air Traffic Management Missions Security (B5)</td>
<td>Radar Information (C14)</td>
<td>Weather Data (C15)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Automatic Switching Segments (C16)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Aeronautical Information (C17)</td>
</tr>
</tbody>
</table>

#### 3.3. The Classification of Security

According to the national requirement, "Information Security techniques - Protection Guide of Information security classification level" [5], this paper divides the risk assessment result of information system of ATM network into five levels, respectively: high safe, safer, low safe, dangerous and very dangerous. And the scope of each level represents actual output values of the network, shown in Table 2.

#### 3.4. Risk Assessment Model for ATM Network Based on RBF Neural Network

Radial Basis Function (RBF) neural network is a forward back network base on function approximation theory. The learning of RBF network is equivalent to seek the best fitting plane of training data in multi-dimensional space. Each hidden layer neurons’ transfer functions of RBF neural network constitute a basis function of the intended plane. Then that is how RBF got its name. BP network is a typical global approximation function. Comparing with BP network, RBF network usually has larger scale, but ability of faster learning and good nonlinear approximation.

#### Table 2. The classification of security.

<table>
<thead>
<tr>
<th>Security Level</th>
<th>Low safe</th>
<th>Safer</th>
<th>High safe</th>
<th>Dangerous</th>
<th>Very dangerous</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.85-1.00</td>
<td>0.70-0.85</td>
<td>0.60-0.70</td>
<td>0.45-0.60</td>
<td>0.00-0.45</td>
</tr>
<tr>
<td>Letter</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>E</td>
</tr>
</tbody>
</table>

A RBF neural network model structure with R-dimensional input show in Fig. 2. In which \(||w-P||\) module is the distance of input vector and weight vector. This model use Gaussian function, radbas function, as the transfer function of neurons, whose input is the distance of input vector \(P\) and weight vector \(w\) multiplied by threshold \(b\). Radbas function is a typical radial basis function and its expression is shown in (1).

\[
f(x) = e^{-x^2}
\]  

Center and width of radial basis function neurons are two important parameters. Weight vector \(w\) of neurons identified the center of radial basis function. When the input vector \(P\) and \(w\) overlap, radial basis function achieves maximum output of neurons. The more distance between input vector \(P\) and weight vector \(w\) is great, the more neuron output is small. Neuron threshold \(b\) identified width of radial basis function. The more threshold \(b\) is big, the more attenuation of the function is great when the input vector \(P\) is far away from weight vector \(b\).

![Fig. 2. Risk assessment model for ATM network based on RBF neural network.](image-url)
Although Fig. 2 is similar to BP network with single hidden layer. RBF’s structure and algorithm is essentially different from BP. From the input space to hidden space transformation is nonlinear, but from the hidden space to the output layer space transformation is linear. The role of hidden layer units is equivalent to do a transformation for input mode. Transform the low-dimensional input data mode to high-dimensional space in order to facilitate classification.

4. Experimental Simulation and Test

4.1. Modeling and Parameter Settings

This paper uses training samples from risk assessment indicator system as input and the level of security as output, using function newrb in MATLAB artificial neural network toolbox to train the network with the learning samples [4-6].

Function newrb (2) utilizes iterative method to design RBF network. At the beginning, the number of hidden layer neuron is zero. And then hidden layer increases one neuron in each iterations. In the first, the network simulates and finds out the input sample vector corresponding to the maximum output error. Secondly, add a neuron into the hidden layer and set the input vector as weight vector. At last, modify the weights of the linear layer until mean square error cuts down to target error or the number of hidden layer neuron reaches the maximum times of iteration. Function newrb calls in the form of

\[
\text{net} = \text{newrb} (\text{P}, \text{T}, \text{goal}, \text{spread}, \text{MN}, \text{DF})
\]

The parameters are shown in Table 3.

In order to validate the performance of risk assessment model of the network, this paper uses simulation environment in MATLAB to train samples.

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Parameter value</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>17 factors</td>
<td>Input vector</td>
</tr>
<tr>
<td>T</td>
<td>desired output</td>
<td>Expected output by expert scoring</td>
</tr>
<tr>
<td>goal</td>
<td>0.001</td>
<td>Network mean square error</td>
</tr>
<tr>
<td>spread</td>
<td>0.9</td>
<td>Extended constant</td>
</tr>
<tr>
<td>MN</td>
<td>12 (default)</td>
<td>The maximum number of neurons</td>
</tr>
<tr>
<td>DF</td>
<td>1</td>
<td>Frequency training process on show</td>
</tr>
</tbody>
</table>

One of most important parameter of newrb function is spread, which is the distribution density of RBF function and can impact greatly on performance of the network. So it needs to adjust values of the spread to reach the ideal accuracy in the process of the network design. As following, the spread is respectively set as 0.1, 0.3, 0.5, 0.7 and 0.9. Validate and compare different values of spread which impact on the degree of risk assessment. It is supposed that network mean square error is 0.001. As shown in Fig. 3, i.e. approximate error curve figure of risk assessment model for ATM network based on RBF neural network.

As we can see from Fig. 3 the cyan blue line whose spread is 0.9 has the best performance and the blue line whose spread is 0.3 has the biggest error. Therefore, this paper chooses the optimal value of spread 0.9 which is used in the risk assessment. When the network parameter spread is 0.9, the convergent of risk assessment model for ATM network based on RBF network is shown in Fig. 4. It can be seen from the Fig. 4 that when the training to step 2, the network error reaches set error requirement. According to the principle that increasing a neuron to hidden layer every iteration, the well trained RBF network only has two hidden layer neurons, whose training speed is very fast.

To test the performance of network after training, this paper analyses the simulation output vector and the target vector with the linear regression analysis method, and treats the correlation coefficients of the target vector and model output vector as an important performance evaluation indicators.

![Fig. 3. Approximate error curve of evaluation model.](image)
When the network performance is good enough to some extents, the value of network model simulation should be equal to that of actual network output, i.e. the regression line is in the first quadrant coordinate axis on the diagonal. At this time, the intercept is equal to 0; slope equal to 1; fitting degree is equal to 1. Finally, we get the linear regression equation by the value of RBF neural network simulation and the actual output:

\[
\text{Output} = 0.99 \times \text{Target} + 0.0093 \\
(R = 0.99371) \tag{3}
\]

Training results shows that: Risk assessment model, which is proposed by this paper, for ATM networks based on RBF neural network can reach the error specifications.

### 4.2. Testing

This paper uses 5 groups of results from experts’ evaluation to test the well trained network and validate the effect of the risk assessment model.

Algorithm is realized using MATLAB language and the test results can be in Table 4. The maximum relative error between output and the desired output value of samples is less than 2.47%. The output level of security and the expected output is almost the same.

<table>
<thead>
<tr>
<th>Output Level</th>
<th>Desired output</th>
<th>Actual output</th>
<th>Relative error%</th>
<th>Output level</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>0.870</td>
<td>0.875</td>
<td>0.57</td>
<td>A</td>
</tr>
<tr>
<td>E2</td>
<td>0.828</td>
<td>0.846</td>
<td>2.12</td>
<td>B</td>
</tr>
<tr>
<td>E3</td>
<td>0.847</td>
<td>0.823</td>
<td>0.63</td>
<td>B</td>
</tr>
<tr>
<td>E4</td>
<td>0.839</td>
<td>0.837</td>
<td>0.26</td>
<td>B</td>
</tr>
<tr>
<td>E5</td>
<td>0.831</td>
<td>0.852</td>
<td>2.47</td>
<td>A</td>
</tr>
<tr>
<td>average</td>
<td>0.843</td>
<td>0.847</td>
<td>1.21</td>
<td></td>
</tr>
</tbody>
</table>

The risk assessment model constructed by this paper bases on RBF neural network can effectively conduct a risk assessment. Test results show that the proposed risk assessment model based on RBF neural network for ATM network is certain feasible. The network model has many advantages, such as faster learning, less numbers of hidden layer neurons, simpler structure, better accuracy and smaller errors. The test results fit well with the actual situations demonstrating that the model has some certain of practicality.

### 5. Conclusions

This paper states with the possible threats and vulnerabilities of civil aviation ATM network and list out the significance of risk assessment for ATM network, finally, proposes risk assessment model based on RBF neural network. According to the characteristics of information security risk on civil aviation ATM network, we put the influencing factors as input of the RBF neural network and the level of security of risk assessment as the network’s output, establishes risk assessment model based on RBF neural network for ATM network. Its nonlinear processing capacity breaks through the limitations of existing evaluation methods, solves the hard problems, such as the information of general assessment methods are incomplete and contradictory and the nonlinear relationship between factors is difficult to assess. Therefore, RBF neural network is an effective way to achieve risk assessment for more comprehensive factors.

By using RBF neural network model, this paper solves influence to risk assessment from a mixed variety of complex factors of ATM network, and use simulation and validation methods to validate the proposed model. Simulation results show that the designed model meet the characteristics of risk assessment and accurately reflect the situation of the threats of ATM network. The proposed risk
assessment model can ensure civil aviation security incident prevention in order to guarantee civil aviation information system to operate safely and efficiently.

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