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Risk Warning Technology of Large Passenger Flow in Subway Station

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Abstract: This paper identifies the safety risk factors of large passenger flow in subway, select the core factors according to the Rough Set Theory, and establishes a systematic risk warning framework of large passenger flow. The early warning level and threshold of subway passenger flow were defined, and the risk early warning model based on ANNs was established, which provided a reference for the risk early warning work of subway station passenger flow evacuation.

Keywords: Subway transportation, Early warning of risks, Self-organizing competition, Network of nerves.

1. Introduction

Subway carries a large number of passengers, so it is very dangerous to have an accident. Currently, subway accidents in the world mainly include: Fire, earthquake, flood, explosion, poisonous gas, terrorist attack, harmful material leakage, train conflict, train derailment, train disintegration, casualties outside the road, sudden large passenger stampede, important equipment failure/damage and other accidents interrupting operation.

2. Materials and Methods

2.1. 1Risk factors

By means of Delphi method, scenario analysis method and checklist method, the risk factors of subway operation safety are systematically identified, and the factors influencing the safety risks of subway with large passenger flow are established.

The combined risk value can be calculated by formula (1).

$$Z_j = \frac{1}{m}\sum_{i=1}^{4}(w_i\sum_{k=1}^{m}F_{ijk}) \quad Z = \frac{1}{n}\sum_{j=1}^{n}Z_j \tag{1}$$

Z_j is the risk value of the J emergency in urban subway operation, Z is the comprehensive risk value of urban subway operation. F_{ijk} is the risk value assigned by the k expert to the accident j caused by index i. The safety risk level is divided into super high risk (80≤Z≤100); High risk (60≤Z≤80); Medium risk (40≤Z≤60); Low risk (20≤Z≤40); Ultra-low risk (Z≤20).

Questionnaire survey was carried out on the operation management staff of Dalian Metro, then, I summarized and analyzed the results of subway accidents , and calculated the comprehensive risk value, and the conclusion was reached through analytic hierarchy process (AHP).

2.2. Warning level and threshold definition

The warning level of major passenger flow adopts the four-level (red, orange, yellow and green) warning mode. Different levels of large passenger flow warning will indicate the probability of passenger casualties and different emergency measures taken after the alarm.

Real-time passenger flow and passenger flow density can be monitored by means of infrared, monitoring, laser and sensor. By simulating the field situation of Xi 'an Road Station in Dalian, this paper makes quantitative judgment through passenger flow, crowded coverage area of passenger flow, proportion of passenger flow retention and crowd flow, determines the warning threshold: Level 4 (green) means that the load rate is more than 80%, there is no stranded crowd in the station hall, the traffic is smooth, it needs to pay attention to the station information and status monitoring, and timely response; Level 3 (yellow) Full capacity ratio is greater than 100%, platform passengers stranded, slow traffic, need to open more temporary train, scientific guide passenger flow; There are stranded passengers in the platform of Level 2 (Orange), the passenger flow density of the station hall is high, the load rate reaches 120%, and the traffic is slow, so it is necessary to limit the inbound passenger flow and arrange trains to stop and wait. Level 1 (red) platform station hall passenger flow is full, passenger load rate is more than 130%, affecting traffic,we should closed the station ,stop the train, only out and not in.

2.3. Risk early warning framework

The risk of subway mass passenger flow transportation is the knowledge system S, and a discussion domain U is set, namely several accident instances; C is the conditional attribute, namely the influencing factor index; D is the decision-making attribute, namely whether it affects the transportation and the level of influence; V is the set of attribute values, within a certain range. Data set analysis can be conducted based on 10 accident instances, and 20 influencing factors can be classified as: Staff skill level assessment, passenger emergency handling ability assessment, crowd flow, total passenger flow, passenger congestion coverage area, passenger flow retention ratio, male to female ratio, middle-aged young people and elderly children ratio, normal passengers and passengers with luggage ratio, lighting deficiency, communication failure, disaster prevention alarm and environmental monitoring system, AGM, evacuation channel, natural environment, social environment , Personnel factors, equipment management, regulations, emergency management techniques are compiled as conditional attributes a, b, c...... t, the equivalent class of each conditional attribute, namely:

$$U|（a）=\left\{\{1,2,4,5\},\{3\},\{6,7\}\{8,9,10\}\right\}$$

According to the simplification of C. To derive the classification from the equivalence relation family $C=\{a,b,c,...,t\}$, it can be concluded that the attributes f and h can be omitted, $C'=\{a,b,c,d,e,g,i,..., t\}$,

namely $\text{CORE（C）}=\{a,b,c,d,e,g,i,..., t\}$.

Therefore, the selected core risk warning indicators include personnel S1 (subway personnel skill level assessment S11, passenger emergency handling ability assessment S12, crowd flow S13, total passenger flow S14, crowded area S15, passenger retention ratio S16, and crowd composition state S17). Environment S2 (natural environment S21, social environment S22); Equipment S3 (insufficient lighting S31, communication failure S32, disaster prevention alarm and environmental monitoring system S33, AGM S34, evacuation channel S35); Management S4 (Personnel factors S41, Equipment Management S42, Regulations S43, Emergency Management Technology S44).

Table 1. Core risk pre-warning indicators

Category	Indicators	Category	Indicators
PersonnelS1	Subway personnel skill level assessment S11	EquipmentS3	Insufficient lighting S31
	Passenger emergency handling ability assessment S12		Communication failure S32
	Crowd flow S13		Disaster prevention alarm and environmental monitoring system S33
	Total passenger flow S14		AGM S34
	Crowded area S15		Evacuation channel S35
	Passenger retention ratio S16	ManagementS4	Personnel factors S41
	Crowd composition state S17		Equipment Management S42
EnvironmentS2	Natural environment S21		Regulations S43
	Social environment S22		Emergency Management Technology S44

3. Results and Discussion

Establish ANN's self-organizing competition network technology security risk warning model:

The evaluation parameters of the four models were analyzed to form a 4-dimensional vector. Collect 3 samples of each failure mode, 12 training samples in total.

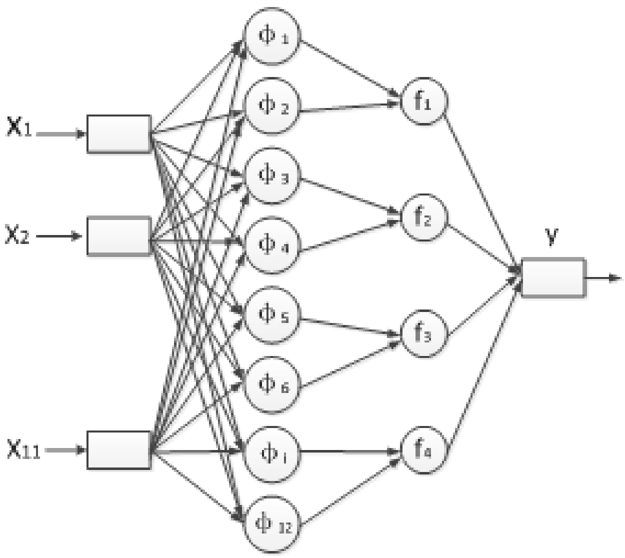

Figure 1. Probabilistic neural network model

When neuron j has multiple inputs $x_i(i=1,2,...m)$ and a single output y_j, the relationship between input and output can be expressed as Formula(2).

$$\begin{cases} s_j=\sum_{i=1}^{m} w_{ij}x_i-\theta_j \\ y_j=f(s_j) \end{cases} \tag{2}$$

Where j is the threshold value, w_{ij} is the connection weight factor from neuron i to neuron j, and f() is the transfer function, or excitation function.

The neural network model consists of 12 input samples, each sample is 11 - dimensional vector, and the probabilistic neural network structure is established. The input layer of the neural network consists of four neurons, and the input feature vector is an 11-dimensional vector. The radial base consists of 12 neuron nodes, and each node corresponds to an input training sample. The hidden layer contains 4 neurons, corresponding to 4 classification patterns. In the radial base, the nodes corresponding to the training samples belonging to this mode are connected with it, while the nodes corresponding to the samples not belonging to this mode are not connected. After summing the input of the hidden layer, the maximum value of the hidden layer neurons is found and the corresponding category number is output.

Define 8 test samples:

Table 2. Training sample of mode determine

	No.	C	P	S	R	V	ρ	E	M	F	A	D
Model1	1	1	1	100	0.04	1.1	0.1	1	0	0	1	1
	2	1	0.5	120	0.05	1	0.2	1	0	0	1	1
	3	0.5	0.7	200	0.07	0.9	0.2	1	0	0	0	1
Model2	4	0.5	2.5	700	0.3	0.8	0.5	1	0	0	1	1
	5	0.5	3	700	0.3	0.8	0.6	1	1	1	1	0
	6	1	5	800	0.4	0.7	0.7	0	0	0	1	1
Model3	7	0.5	8	1000	0.6	0.6	1	1	1	1	1	1
	8	0	9	2000	0.8	0.5	1.1	0	1	1	0	0
	9	0.5	9	2000	0.7	0.4	1.1	0	0	0	0	0
Model4	10	0	12	3000	0.9	0.3	1.3	0	1	1	0	0
	11	0.5	12	3500	1	0.2	1.3	0	1	1	0	0
	12	0	13	4000	1.2	0.2	1.4	1	1	0	1	1

Among them, the skill level of subway personnel was evaluated as C (0,0.5,1 three-level quantification); Passenger flow P (thousand people per hour); Coverage area of crowded passenger flow S (square meters); Passenger flow retention ratio R (retain 1 decimal place); Crowd flow rate V (m/s); Area density ρ (person/square meter); The advantages and disadvantages of the environment E (0,1 two-level quantization); Monitoring equipment failure M (0,1 two-level quantization); Whether the evacuation equipment is faulty F (0,1 two-level quantization); Whether the management is perfect A (0,1 two-level quantification); Whether emergency response D is appropriate (level 0,1 quantification).

4. Results and Analysis

The diagnostic process includes sample definition, sample normalization, network model creation, testing, and result display. The script can be executed to complete the network creation and simulation, and the output result is obtained in the command window. The actual category matches the judgment category.

Table 3. The test sample

No.	C	P	S	R	V	ρ	E	M	F	A	D	Model
1	0.5	9	1800	0.7	0.4	1	0	1	0	0	1	Model3
2	1	0.4	200	0.05	1	0.2	0	0	1	0	1	Model1
3	1	0.5	80	0.05	1	0.1	1	0	0	1	1	Model1
4	0.5	3	650	0.3	0.75	0.55	0	0	0	1	1	Model2
5	0.5	12	4000	1	0.2	1.2	0	0	1	0	0	Model4
6	0	9	2200	0.8	0.5	1.1	0	0	0	1	0	Model3
7	1	5	750	0.4	0.7	0.7	1	0	0	1	1	Model2
8	0	13	3000	1.2	0.2	1.4	1	0	0	0	0	Model4

The diagnosis made by probabilistic neural network is basically correct and the model can be applied.

5. Conclusions

In practical application, the tested data is used for input, Matlab self-organized competitive network model for simulation warning analysis, and the output result is used as the alarm level.

Established an input parameter, and the parameter attributes include passengers (travel time, feature ratio), traffic (train interval, loading and unloading time, traffic organization mode), passenger flow (peak section passenger flow, inbound and outbound passenger flow, train full load rate, and retention density. Passenger flow density), space use (aisle width, congestion area, space utilization rate), transfer (transfer distance, transfer time, transfer coefficient), node services (gates, stairs, elevators, horizontal walkways, ticketing facilities, security facilities) and other parameters.

The output is associated with the established warning levels: red, orange, yellow, and green.

This early warning model is inspired by the fault diagnosis model of diesel engine and adopts the method of self-organizing competitive neural network, which has not been studied before in the subway passenger flow distribution. It can be applied to a wide range of applications. In the future, it can be applied to a more intelligent platform to shorten the early warning and gain more time for evacuation, which has a good reference for the research on the safety risks of subway passenger flow distribution.

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