Optimization and integration method for railway freight stations based on a hybrid neural network model

Yan Sun, Maoxiang Lang*, Danzhu Wang

School of Traffic and Transportation, Beijing Jiaotong University, Haidian District, 100044 Beijing, P.R. China

Received 12 June 2014, www.cmnt.lv

Abstract

Given to the current problems existing in the operation of railway freight stations and the entire railway freight transport network, in order to integrate the railway freight stations and optimize the traditional railway freight transport mode, we first propose a strategy on the optimization and integration for railway freight stations, then design a hybrid neural network model to recognize the operating performance of each railway freight station by classifying them into four ranks based on the proposed strategy. The characteristic of the proposed model is its combination of the respective advantages of unsupervised learning algorithm based neural network and supervised learning algorithm based neural network. Finally, an empirical study from Hohhot Railway Administration is given to verify the feasibility of the proposed model. The simulation results of the empirical study indicate that (1) the accurate recognition of training samples has significant influence on the classification result; (2) the proposed model can recognize the operating performance of the railway freight stations under relatively high accuracy.

Keywords: Railway Freight Station, Optimization and Integration, Hybrid Neural Network Model, SOM Neural Network, Probabilistic Neural Network

1 Introduction

Railway freight stations are the nodes where goods get into or out of the railway network, rail wagons get classified and freight trains get sorted [1]. They play an important role in the railway freight transport organization. And there are enormous railway freight stations dispersed on the wide railway network in China, which provides the freight market with great convenience in a long period. However, with the development of social economy, optimization and adjusttment of industrial structure, and perfection of logistics industry in recent years, the traditional transport organization based on the dispersed layout of railway freight stations cannot adapt the tendency of the freight transport intensive development. Therefore, problems existing in the operation of railway freight stations tend to be obvious, such as insufficient shipment, inefficient operation, and delay of goods transport, waste of transport resources and so no. Railway freight transport hence falls behind compared with other transport modes, for example, highway freight transport. In 2006, China Ministry of Railways of China proposed “Two Integration, One Construction” revolution to overcome these problems. Since then, studies on optimization and integration for railway freight stations have been placed great emphasis on.

Optimization and integration for railway freight stations can be considered as a typical classification problem based on the operating performance of each railway freight station. According to their operating performance, railway freight stations can be classified into different ranks. Railway freight stations in different ranks will play different roles in the railway freight transport network in order to make up a flatter railway network system. Railway freight transport organization can be then further optimized based on this flatter railway network.

As for the optimization and integration methods, besides qualitative methods, some quantitative methods have been applied in the optimization and integration for railway freight transport resources, including Analytical Hierarchy Process (AHP) analysis [2, 3], fuzzy comprehensive evaluation method [4-6] and Pareto (also named ABC) analysis [7]. However, these methods rely on individual experiences of evaluators to some extent and have less comprehensive consideration of various influencing factors. The limitations of these methods in the calculation are apparent, especially when the scale of data and samples is tremendous. Therefore, study on optimization and integration for railway freight stations still has a large research potential.

Recent studies on the classification problem in other research fields have attached great importance to artificial intelligence, due to its well capacity of processing large size of data, high calculation efficiency and accuracy. As one of the most mature and widely used artificial intelligence methods, artificial neural networks have been proved well feasible in many relevant studies. Some studies are presented as follows.

Azami et al. [8] focused on the BP neural network for the recognition of the quality of GPS satellites. In this study, taking geometric dilution of precision as the evaluation index, the GPS satellites was classified into six classes by six modified BP neural networks, and the resilient BP neural network proved the highest accuracy and the least calculation time in the simulation. Park and Cho [9] studied on

*** Corresponding author** e-mail: langmaoxiang@yeah.net

the welding quality evaluation and applied LVQ neural network and BP neural network to classify electrode force patterns into five standard patterns. The experiment result in this study indicated the success rate for the testing samples of BP neural network was higher than LVQ neural network, while its calculation time is longer than LVQ neural network. Tan and Du [10] designed a feature extraction model and combined it with RBF neural network to perform the remote sensing image classification. The classification accuracy of the proposed model was verified by comparing with BP neural network and minimum distance classification method. Tambouratzis et al. [11] adopted hierarchical feature map to optimize the basic SOM neural network. In this study, texts classification problem based on their register and author style was used to verify the feasibility of the modified SOM neural network model. Ryoo et al. [12] described a fuzzy neural network and temperature response curve fitting based method to classify the unknown materials. In this experiment for three materials, the superiority of the modified method was verified that the agreement between measured curve and approximated curve was suitable. Using gene expression data, Sun et al. [13] applied discrete wavelet transform-based feature extraction and probabilistic neural network jointly to classify tissues into six classes. In the empirical study, the proposed DWT-based method possessed higher accuracy than the no DWT methods. Wang et al. [14] presented a novel tumor classification approach by combining probabilistic neural network with a neighborhood rough set model. In this study, tumor was classified into five classes by different gene datasets. 4-fold accuracy of colon dataset, leukemia dataset, and SRBCT dataset was up to 96.77%, 100% and 100%, respectively. Debska and Guzowska-Świder [15] proposed an artificial neural network based classification model to recognize the quality of beer. In this study, thirteen elements were selected as the characteristic of the quality of beer. RBF neural network model and MPL neural network model were applied to undertake the classification. The simulation result indicated that artificial neural network techniques allowed then discrimination between qualities of beer samples with up to 100% of correct classifications. Huang and Pan [16] used a probabilistic neural network to carry out the classification of operating performance of the enterprises. In this study, the input data of the neural network were selected by data mining technique. After inputting fifteen variables from five aspects, probabilistic neural network could give higher classification accuracy compared with BP neural network.

On the basis of the previous studies above, in Section 2, we propose a strategy on optimization and integration for railway freight stations in Section 2. In Section 3, we analyse the characteristic of supervised learning algorithm based neural network and unsupervised learning algorithm based neural network. In Section 4, by combining the respective advantages of the two kinds of neural networks, we definite a hybrid neural network model for the recognition of operating performance of the railway freight stations and present its modelling process. In Section 5, an empirical study from Hohhot Railway Administration is used to verify the feasibility of the proposed model and explain the importance of the accurate recognition of training samples. Finally, the conclusions of this study are drawn in Section 6.

2 Strategy on optimization and integration for railway freight stations

2.1 OPERATING PERFORMANCE OF RAILWAY FREIGHT STATIONS

Due to the difference of the environment where a railway freight station locates and the transport resources it owns, railway freight stations will perform different operating performances in the railway freight transport organization.

In this study, we use four ranks to distinguish the operating performance of the railway freight stations by referring some relevant studies on enterprise management [16, 17]. Operating performance rank designed in this study is as shown in Table 1.

TABLE 1 Operating Performance Rank of Railway Freight Stations

Rank	Operating Performance	Representation
I	Excellent	(1,0,0,0)
II	Good	(0, 1, 0, 0)
III	Medium	(0, 0, 1, 0)
IV	Poor	(0, 0, 0, 1)

In order to describe the characteristic of a railway freight station and further apply it to recognize which rank the operating performance of this railway freight station belongs to, we mainly take four aspects into consideration, including social environment factors, freight operation factors, transport location condition factors and freight transport facility factors, and establish an evaluation index system, which is as shown in Figure 1. If the i^{th} (i=1, 2, …, 16) index is represented by x_i, the characteristic of a railway freight station can be described by an index vector $X = (x_1, ..., x_i, ..., x_{16})$.

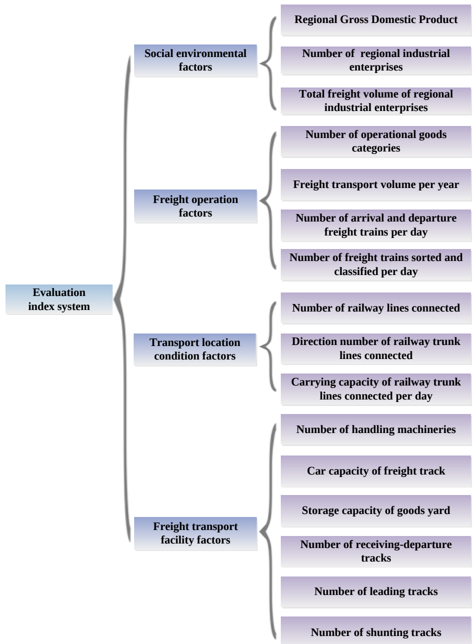

FIGURE 1 Evaluation Index System of the Operating Performance of Railway Freight Stations

2.2 OPTIMIZATION FOR THE RAILWAY FREIGHT TRANSPORT ORGANIZATION BASED ON THE OPERATING PERFORMANCE OF RAILWAY FREIGHT STATIONS.

Based on the ranks in Table 1, railway freight stations are classified into 4 ranks. Due to the poor operating performance of the railway freight stations in Rank IV, they should be closed and the transport resources occupied by them should be recycled by railway freight stations in Rank I, II and III. As for railway freight stations from Rank I to III, the roles they play in the railway network are given as follows.

Railway freight stations in Rank I are the 1st layer nodes in the railway network. They are the sites where through freight trains from different directions get sorted or classified. They locate in the crossing of railway trunk lines and possess adequate facilities corresponding with the sorting and classification of the freight trains. Railway freight stations in Rank II are the 2nd layer nodes in the railway network. They organize the highway-railway intermodal transport and undertake loading and unloading, storage, sorting, flitting and distribution of goods. Therefore, railway freight stations in Rank II should have well railway brunch line transport conditions and possess adequate facilities including handling machines, freight tracks and goods yard, as well as better freight operation environment. Railway freight stations in Rank III are 3rd layer nodes. They are the most widespread nodes in the railway freight network. These stations are the end of the internal freight transport chain. Their main operations include providing pickup and home-delivery services and conducting the freight marketing business. The railway freight network can be divided into several freight organization zones composed of "one 1st layer railway freight station, a few 2nd layer railway freight stations and several 3rd layer railway freight stations" as shown in Figure 2.

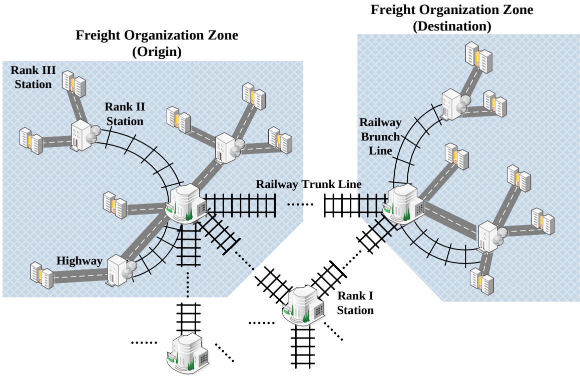

FIGURE 2 Optimized Operation Mode of Railway Freight Transport Network

According to the analysis above, the operation mode of railway freight transport network can be optimized as shown in Figure 3. Figure 3 indicates the basic transport organization mode in the railway freight transport network. In the transport organization, railway transport plays a dominated role and is the main force of the transport organization. Highway transport is the supplement and its participation can enhance the flexibility of the transport organization and extend the freight transport service chain as well. Different composite modes can be selected based on the goods volume and the centralization degree of the goods flow destinations.

In the optimized operation mode, the dispersed railway freight transport resources can be integrated, the advantage of highway and railway in short and long distance transport can be taken, and the operation of railway freight transport can be simplified.

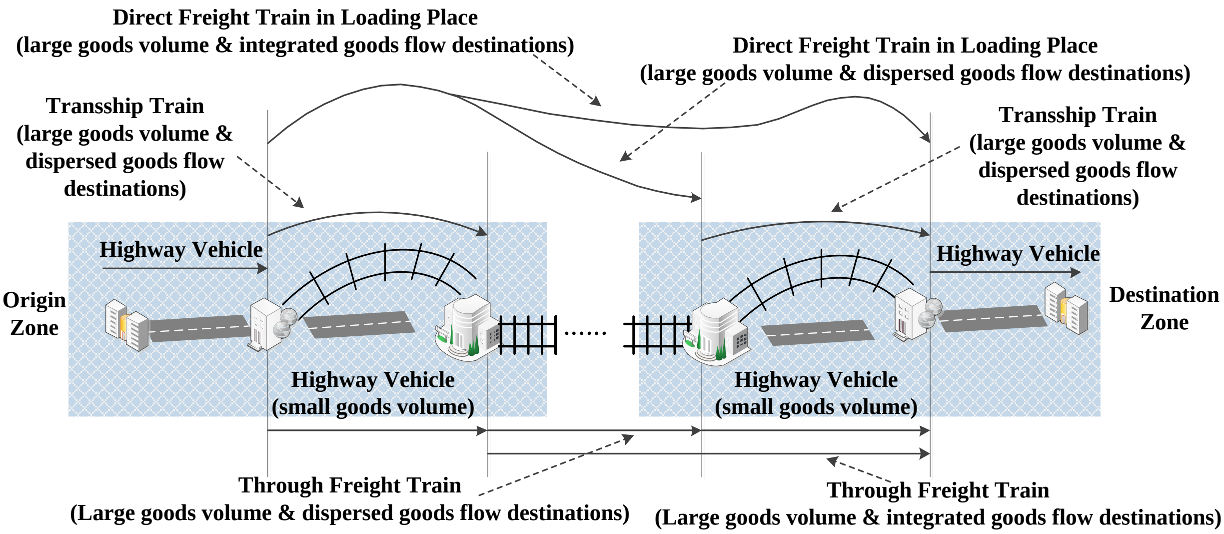

FIGURE 3 Transport Mode in the Optimized Railway Freight Transport Network

3 Supervised and unsupervised learning algorithm based neural networks

According to the learning algorithm, artificial neural networks can be mainly classified into 2 categories, including supervised learning algorithm based neural networks and unsupervised learning algorithm based ones. Their respecttive characteristic is stated as follows.

3.1 SUPERVISED LEARNING ALGORITHM BASED NEURAL NETWORKS

The common characteristic of the supervised learning based neural networks is the requirement of their learning process for the training samples whose outputs should be determined in advance. Once the training samples and their outputs are given, the classification result will be a certainty. Therefore, the classification accuracy depends on the recognition of the training samples. In the previous study, the training samples were usually selected by individual experiences, which may result in the conflicts or mistakes due to different experiences and will reduce the classification accuracy, especially when the classification ranks are various and the data size of the experimental sample set is tremensdous.

Supervised learning based neural networks include BP neural network, linear neural network, RBF neural network and its deformation modes (generalized regression neural network and probabilistic neural network) and so on.

Compared with other neural networks, probabilistic neural network has many advantages in the classification, such as simplified operation, faster convergent rate, higher stability and better fault tolerance [18, 19].

3.2 AN UNSUPERVISED LEARNING ALGORITHM BASED NEURAL NETWORK

SOM (Self-Organizing Map) neural network adopts an unsupervised and competitive learning algorithm to map the multi-dimensional data onto a 2-dimensional map [20, 21], which can classify the samples into several clusters without determining the training samples and their expected output in advance and can avoid subjective affect from individual experiences consequently. However, the output value of the neural network depends on its parameter setting, including the learning rate and the number of competitive neurons and maximum iteration times, which results in the uncertainty of the classification result.

4 Modelling of the hybrid neural network model for the recognition of the operating performance of railway freight stations

4.1 DEFINITION OF THE HYBRID NEURAL NETWORK MODEL

Generally, the selection of training samples and recognition of their outputs are determined by the researchers, for example, studies presented in [8-16]. Due to the different experience of different researchers, the selection and recognition of the training samples may be various, which leads to conflicts and even mistakes existing in the classification result. Sometimes, the wrong recognition of some training samples leads to the relatively low classification accuracy. It easily happens especially when there is tremendous information to be processed.

Therefore, based on the analysis in Section 3, we design a hybrid neural network model to recognize the operating performance of the railway freight stations. The hybrid neural network consists of two parts: SOM neural network for the preliminary recognition and probabilistic neural network for the accurate recognition. The respective advantages of the supervised learning algorithm based neural network and the unsupervised learning algorithm based neural network can be combined in this model.

According to the preliminary recognition result by SOM neural network, we can select accurate recognized samples as training and testing samples, and use them to train and test the probabilistic neural network. Finally, a well-constructed probabilistic neural network can be gained to recognize the validation samples. The block diagram of the hybrid neural network is as shown in Figure 4.

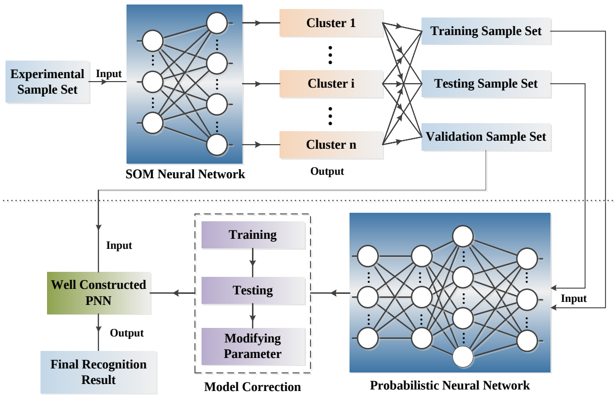

FIGURE 4 Block Diagram of the Hybrid Neural Network Model

4.2 MODELLING PROCESS OF SOM NEURAL NETWORK

SOM neural network is a 2-layer artificial neural network composed of an input layer and a competitive layer. The learning process of SOM neural network consists of three sub processes: competition process, cooperation process and adaption process [21]. Its modelling process is presented as follows.

Step 1. Initialize the SOM neural network.

In this step, the number of competitive neurons (n) and the number of maximum iteration times (T) are determined. Weights connecting the input neurons to the competitive neurons are set in range [0, 1] randomly. In the t^{th} training process, w_{ij}^t is the weight connecting the i^{th} input neuron to the j^{th} competitive neuron, so the weight vector of the j^{th} competitive neuron is $W_j^t = (w_{1j}^t, ..., w_{ij}^t, ..., w_{mj}^t)$, where m is the number of input neurons and equals the number of the evaluation indexes. In this study, m=16.

Step 2. Input the index vector X of a railway freight station by the input neurons.

Step 3. Calculate the Euclidean distance between X and W_j^t by Eq.1.

$$dist_j^t = \left\| X - W_j^t \right\| = \sqrt{\sum_{i=1}^{m} (x_i - w_{ij}^t)} \,, \quad j = 1, 2, .., n \tag{1}$$

The Euclidean distance reflects the degree that a competitive neuron matches the index vector of a railway freight station. It will be configured as a parameter in the next step.

Step 4. Gain the winning competitive neuron and its neighbour neuron set.

In this step, if the Euclidean distance between the index vector and the weight vector of the j^{th} competitive neuron satisfies Eq.2, the j^{th} competition neuron is defined as the winning neuron and can be represents by j^*. Its neighbour neuron set $N_{j^*}^t$ can be then determined.

$$dist_j^t = \min\{dist_k^t\}_{k=1}^{n} \,, \tag{2}$$

Step 5. Modify weights by Eq.3.

$$w_{ik}^{t+1} = \begin{cases} w_{ik}^t + \alpha_t \cdot (x_i - w_{ik}^t) & k \in \{j^*, N_{j^*}\} \\ w_{ik}^t & else \end{cases} \,, \quad k = 1, 2, ..., n \quad i = 1, 2, ..., m \tag{3}$$

where α_t represents the learning rate of the neural network and $\alpha_t \in [0,1]$. Its value decreases with the iteration process.

Step 6. Judge the termination condition is attained or not.

If $t<T$, set $t=t+1$, and then repeat Step 2 to Step 6, otherwise stop the algorithm and give the output value of the input index vector X.

Step 7. Calculate the output value of the competitive layer.

In this step, the output value of the k^{th} competitive neuron and the entire competition layer can be calculated by Eq.4 and Eq.5, respectively.

$$y_k^t = \begin{cases} 1 & k \in \{j^*, N_{j^*}\} \\ 0 & else \end{cases} \,, \quad k = 1, 2, ..., n \tag{4}$$

$$y_t = \sum_{k=1}^{n} y_k^t \,. \tag{5}$$

When inputting the index vectors of different railway freight stations into the neural network, if the output values of the competition layer are equal, these railway freight stations belong to the same rank, otherwise they belong to different ranks.

4.3 MODELLING PROCESS OF PROBABILISTIC NEURAL NETWORK

Probabilistic neural network is a 4-layer feed-forward neural network composed of an input layer, a pattern layer, a summation layer and an output layer. It is a type of classifier based on Bayesian decision and Parzen estimation [22]. Its modelling process of is presented as follows.

Step 1. Input the index vector X of a railway freight station by the input neurons whose number equals the number of evaluation indexes.

Step 2. Calculate the output value of the pattern neurons.

In this step, the ith pattern neuron corresponds with the i^{th} training sample X_i. Using radial basis function as its transfer function, the output value of the ith pattern neuron can be calculated by Eq.6.

$$y_{P_i}(X) = \exp(-\left\| X - X_i \right\|^2 / 2\delta^2) \,, \quad i = 1, 2, ..., n \tag{6}$$

where n represents the number of training samples.

Step 3. Calculate the output value of summation neurons.

Weights connecting the i^{th} pattern neuron to the j^{th} summation neuron are set as Eq.7.

$$w_{ij} = \begin{cases} 1 & training\ sample\ i \in Rank\ j \\ 0 & else \end{cases} \,, \quad j = 1, 2, ..., k \quad i = 1, 2, ..., n \tag{7}$$

where k represents the number of operating performance ranks.

Using $y_{P_i}(X)$ $(i = 1, 2, ..., n)$ as its input, the summation neuron will do weighted summation and output the value by Eq.8.

$$y_{S_j}(X) = \sum_{i=1}^{n} [w_{ij} \cdot y_{P_i}(X)] \,, \quad j = 1, 2, ..., k \tag{8}$$

Step 4. Gain the classification results by output neurons.

The probability of railway freight station Z $\in$ Rank j can be calculated by Eq.9.

$$P(R_j \mid Z) = \frac{P(Z \mid R_j) \cdot P(R_j)}{P(Z)} \,, \tag{9}$$

where $P(Z \mid R_j)$ represents the conditional probability of X, P(Z) is a constant, which has no effect on the classification results. $P(R_j)$ represents the prior probability of Rank j, and can be calculated from training sample set by Eq.10.

$$P(R_j) = \frac{n_j}{n} \,, \tag{10}$$

where n_j represents the number of training samples that belong to Rank j.

Parzen estimation is applied to estimate the unknown $P(Z \mid R_j)$ by the training sample set according to Eq.11.

$$P(Z \mid R_j) = \frac{\sum_{i=1}^{n} \exp(-\|X - X_i^j\|^2 / 2\delta^2)}{\sqrt{(2\pi)^2 \cdot \delta^d \cdot n_j}} \\ = \frac{y_{S_j}(X)}{\sqrt{(2\pi)^2 \cdot \delta^d \cdot n_j}}, \quad (11)$$

where d represents the number of evaluation indexes, δ represents the smoothing parameter, and X_i^j represents the ith training sample that belongs to Rank j.

When all prior probabilities of the railway freight station belonging to each rank are all equal, there is $P(Z \mid R_j) \propto y_{S_j}(X)$. Therefore, according to "winner takes all" algorithm [23], the output value of the output neurons can be determined by Eq.12.

$$y_j(X) = \begin{cases} 1 & y_{S_j}(X) > y_{S_q}(X) \\ 0 & else \end{cases}, \quad (12)$$

$$j, q = 1, 2, ..., m \quad j \neq q$$

Besides, the output values of the probabilistic neural network satisfy Eq.13.

$$\sum_{j=1}^{k} y_j(X) = 1. \quad (13)$$

5 Empirical study: evidence from hohhot railway administration

5.1 DATA COLLECTION AND PRE-PROCESSING

There are 108 railway freight stations managed by Hohhot Railway Administration. Part of their initial data of the evaluation index system are as shown in Table 2.

Before simulation, the initial data should be normalized into range [0, 1] by Min-Max technique (Eq.14) in order to improve the both classification accuracy and calculation efficiency of the hybrid neural network model [24].

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad i = 1, 2, ..., 16, \quad (14)$$

where $x_{\max} = \max\{x_1, ..., x_i, ..., x_{16}\}$ and $x_{\min} = \min\{x_1, ..., x_i, ..., x_{16}\}$. x_i and x_i' represent the data before and after normalization, respectively.

TABLE 1 Initial Data of the Railway Freight Station Samples

Station Name	**1**	**2**	**3**	**……**	**106**	**107**	**108**
	Baotouxi	*Hohhot*	*Fengzhen*	……	*Wuhaixi*	*Ceke*	*Salaqi*
x_1	7417253	2321449	921899	……	1201539	1789072	1511753
x_2	2	13	3	……	9	5	6
x_3	235.6	2050.5	664.7	……	641.1	168.6	1756.9
x_4	4	4	4	……	6	10	5
x_5	299.9	1984.1	700.7	……	699.4	239.3	1767.4
x_6	183	28.6	0	……	101	82	26
x_7	109	18	0	……	18	9	4
x_8	3	2	1	……	2	2	1
x_9	2	2	2	……	2	2	2
x_{10}	122	95	102	……	306	146	102
x_{11}	0	22	0	……	1	1	0
x_{12}	16	127	61	……	57	124	0
x_{13}	0	245	1157	……	4647	0	733
x_{14}	31	26	15	……	7	13	4
x_{15}	4	3	0	……	3	1	1
x_{16}	29	3	2	……	11	6	0

5.2 MODEL SIMULATION

In this study, we use Matlab R2012b to perform the model simulation by a Lenovo laptop with Intel Core i5 3235M 2.60GHz CPU and 4GB RAM. In the SOM neural network simulation, the topology of the SOM neural network is set as shown in Figure 5 and the maximum iteration times is set to 500.

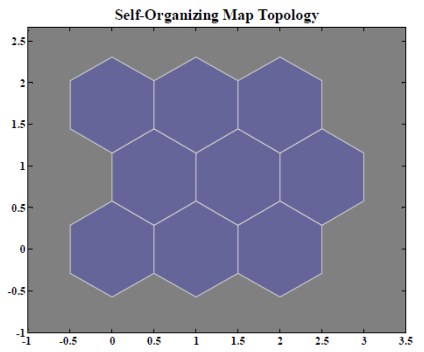

FIGURE 5 Topology of SOM Neural Network

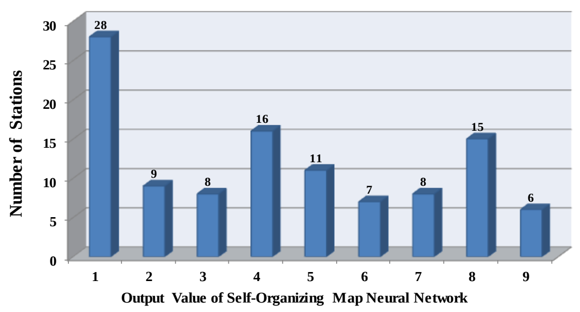

FIGURE 6 Preliminary Recognition Result of the SOM Neural Network

When completing the SOM neural network simulation, the preliminary recognition result is as shown in Figure 6.

Based on the preliminary recognition result, the training samples and testing samples we select are as shown in Table 3. Their expected output corresponds with the binary representation in Table 1.

TABLE 3 Selection of Training Samples and Testing Samples

Rank	Training Samples	Testing Samples
I	Baotouxi, Hohhot, Baotoubei, Linhe	(1) Wuhaixi, (2) Erlian
II	Gongjiban, Baotou, Baotoudong, Fengzhen, Salaqi, Wanshuiquan	(3) Baita, (4) Jiningnan, (5) Saihantala, (6) Wuhaibei
III	Hantaichuan, Hantaichuanbei, Xiangshawan, Erdaoshahe, Gongwusu	(7) Jilantai, (8) Kabuqi, (9) Laoshidan, (10) Lasengmiao, (11) Lasengzhongmiao
IV	Kundulunzhao, Bikeqi, Gongmiaozi, Chasuqi, Toudaoqiao	(12) Tuguiwula, (13) Mingan, (14) Ejina, (15) Xinghe, (16) Daluhao

After several testing, the smoothing parameter we set finally is 1.5. The testing result is as shown in Figure 7. As we can see from Fig. 7, the ratio of correct and wrong number of testing samples is 15:1, which indicates the correct recognition rate is relatively high.

5.3 COMPARISON AND ANALYSIS

In order to verify the importance of the selection of training samples on the recognition result, assume BaotouIVi is mistaken for Rank II, Baotoudong is mistaken for Rank I, Hantaichuan is mistaken for Rank IV, and Toudaoqiao is mistaken for Rank III, then the testing result is as shown in Fig. 8.

The ratio of correct and wrong number of testing samples is 9:7. The comparison between Figure 7 and Figure 8 indicates that the wrong selection of a few training samples can result in the severe reduction of the correct recognition rate of the testing samples, which will further lead to the mistaken in the recognition of the operating performance of the entire railway freight station samples.

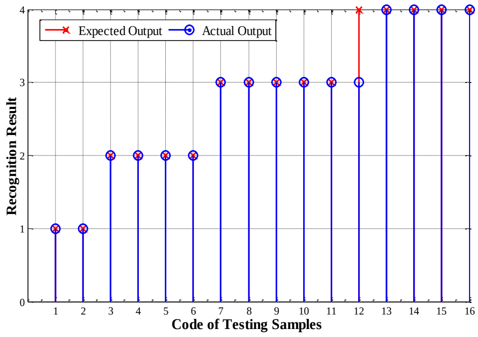

FIGURE 7 Testing Result of the Probabilistic Neural Network

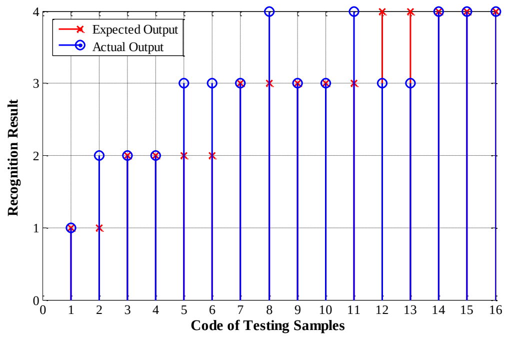

FIGURE 8 Testing Result with Some Wrong Training Samples

In order to verify the performance of the proposed model, we also utilize a 3-layer BP neural network to recognize the operating performance of the testing samples.

The parameters of BP neural network are set as follows. The number of hidden neurons is 40, the number of maximum iteration is 500, and the goal of training accuracy is 10^{-8}. The training performance of BP neural network and its testing result are as shown in Figure 9 and Figure 10, respectively. The ratio of correct and wrong number of testing samples is 13:3, which is lower than the probabilistic neural network.

FIGURE 9 Training Performance of BP Neural Network with Given Parameters

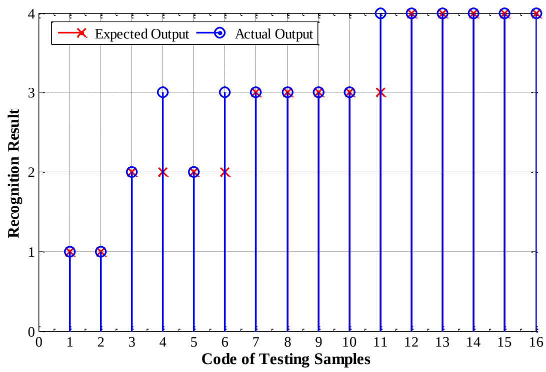

FIGURE 10 Testing Result of BP Neural Network

5.4 FINAL RECOGNITION RESULT

The final simulation result of the hybrid neural network is as shown in Table 4. There are 7 railway freight stations in Rank I, 21 railway freight stations in Rank II, 53 railway freight stations in Rank III, and 27 railway freight stations in Rank IV.

TABLE 4 Operating Performance of the Railway Freight Stations

Rank	Railway Freight Stations	Total Number
I	Baotouxi, Hohhot, Baotoubei, Linhe, Wuhaixi, Erlian, Jining	7
II	Gongjiban, Baotoudong, Baotou, Fengzhen, Salaqi, Wanshuiquan, Baita, Jiningnan, Saihantala, Wuhaibei, Dalahai, Baiyunebo, Ceke, Wuhai, Bayangaole, Jiningnan, Zhenglanqi, Duolun, Zhelimu, Xilinhaote, Zhenglanqi	21
III	Hantaichuan, Hantaichuanbei, Xiangshawan, Erdaoshahe, Gongwusu, Jilantai, Kabuqi, Laoshidan, Lasengmiao, Lasengzhongmiao, Dongxing, Wulateqianqi, Dongshenxi, Guchengwan, Xinxiancheng, Taigemu, Miaoliang, Chagannuoer, Wurigentala, Benjing, Hayehutong, Taosihao, Gujiabao, Minzu, Suji, Zhurihe, Qisumu, Jiangui, Wulashan, Baotounan, Dongshengxi, Eerduosi, Xinjie, Hohhotnan, Suhongtu, Hangjinhouqi, Tukemumiao, Baiyinkulun, Huade, Jinjiadian, Jingpeng, Kailu, Lindong, Linxi, Sanggendalai, Mengtagenlai, Sharinai, Pingandi, Yuzhoudi, Zhelimu, Zhengxiangbaiqi, Baiyunebonan, Xilinhaotexi	53
IV	Kundulunzhao, Bikeqi, Gongmiaozi, Chasuqi, Toudaoqiao, Tuguiwula, Mingan, Ejina, Xinghe, Daluhao, Taigemu, Baiyinchagan, Qixiaying, Baoziwan, Taoboqi, Zhuozishan, Benhong, Wuyuan, Chabuga, Baiyunebonan, Ehensuwu, Bayinhua, Liangsha, Baotumu, Huhewenduer,Nongkensituan, Dalatenan	27

6 Conclusions

In this study, we propose a strategy on optimization and integration for railway freight stations and design a hybrid neural network model to recognize the operating performance of the railway freight stations. Following conclusions can be drawn from the simulation results.

(1) The model can recognize the operating performance of each railway freight station under relatively high accuracy by classifying them into four ranks according to the proposed strategy.

(2) The accurate selection of the training samples has a significant influence on the recognition of the operating performance of the railway freight stations, which can be seen from Figure 7 and Figure 8. The unsupervised learning algorithm base neural network - SOM neural network can help us select the training samples and testing samples accurately, if necessary.

(3) Compared with the widely used BP neural network, probabilistic neural network performs higher recognition accuracy of the operating performance of railway freight stations.

However, in this study, there are still some imperfections presented as follows. Therefore, further research is required.

(1) The transport mode in the optimized railway freight transport network (See in Figure 3) limits to the qualitative analysis. How to organize the freight transport in the optimized railway freight transport network needs to be further analysed quantitatively.

(2) The optimization and integration method for the railway freight stations we propose in this study is currently in the design stage. Its feasibility needs to be further verified in the practical transport production.

Acknowledgments

This study was supported by the National Natural Science Foundation Project (No.71390332-3), the Science and Technology Development Plan of Ministry of Railways (No.2012X012-A) and the Scientific Research Plan of Hohhot Railway Administration (No.2012.2A003) of P.R. China.

References

[1] Caprara A, Malaguti E, Toth P 2011 A freight service design problem for a railway corridor *Transportation Science* **45**(2) 147-62

[2] Zhao Y, Pu Y, Zhong C Z 2005 Optimizing railway logistics structure by fuzzy mathematical theory and analytic hierarchy process *China Railway Science* **26**(3) 119-23 (*in Chinese*)

[3] Wang L L, Zhang X C, Hai T 2007 Weighted Cluster Analysis on Macroscopic Distribution Areas of Railway Dangerous Goods Stations *Journal of the China Railway Society* **29**(6) 101-5 (*in Chinese*)

[4] Lang M X, Zhong M, Liu Z Y 2002 Study on the Closing of Private Railway Sidings by Using Fuzzy Comprehensive Evaluation Method *Chinese Journal of Management Science* **10**(z1) 107-10 (*in Chinese*)

[5] Wang D Z, Li X F, Lang M X 2011 Application of Fuzzy Comprehensive Evaluation on Optimization and Integration of Railway Special Lines *Railway Transport and Economy* **33**(1) 22-6 (*in Chinese*)

[6] Li X F, Lang M X 2010 A Fuzzy Comprehensive Evaluation Model for the Optimization and Integration of the Industrial Railway Sidings *Proceedings 2010 3rd International Conference on Information Management, Innovation Management and Industrial Engineering* 236-9

[7] Wei R 2007 *Study on the adjusting method for the layout of railway freight stations* Master Thesis, Beijing Jiaotong University, Beijing, China (*in Chinese*)

[8] Azami H, Mosavi M R, Sanei S 2013 Classification of GPS satellites using improved back propagation training algorithms *Wireless Personal Communications* **7**(2) 789-803

[9] Park Y J, Cho H 2004 Quality evaluation by classification of electrode force patterns in the resistance spot welding process using neural networks *Proceedings of the Institution of Mechanical Engineers Part B* **28**(B11) 1513-24

[10] Tan K, Du P J 2008 Hyper spectral remote sensing image classification based on radical basis function neural network *Spectroscopy and Spectral Analysis* **28**(9) 2009-13

[11] Tambouratzis G, Hairetakis N, Markantonatou S, Carayannis G 2003 Applying the SOM model to text classification according to register and stylistic content *International Journal of Neural Systems* **13**(1) 1-11

[12] Ryoo Y J, Lim Y C, Kim K H 2001 Classification of materials using temperature response curve fitting and fuzzy neural network *Sensors and Actuators A: Physical* **94**(1-2) 11-8
[13] Sun G M, Dong X Y, Xu G D 2006 Tumor tissue identification based on gene expression data using DWT feature extraction and PNN classifier *Neurocomputing* **69**(4-6) 387-402
[14] Wang S L, Li X L, Zhang S W, Gui J, Huang D S 2006 Tumor classification by combining PNN classifier ensemble with neighborhood rough set based gene reduction *Computers in Biology and Medicine* **40**(2) 179-89
[15] Debska B, Guzowska-Świder B 2011 Application of artificial neural network in food classification *Analytica Chimica Acta* **705**(1-2) 283-91
[16] Huang J C, Pan W T 2010 Forecasting classification of operating performance of enterprises by probabilistic neural network *Journal of Information & Optimization Sciences* **31**(2) 333-45
[17] Zhang L Y, Zhang X 2013 Multi-objective team formation optimization for new product development *Computers and Industrial Engineering* **64**(3) 804-11
[18] Ma Y L, Ma X Z, Feng Z J, Zhang L 2007 Fault diagnosis of high-pressure heater system based on radial basis probabilistic neural network *Journal of North China Electric Power University* **34**(5) 81-4 (*in Chinese*)
[19] Guo X Y 2007 Using probabilistic neural network to diagnose the fault of self-propelled gun engine *Measurement & Control Technology* **26**(8) 804-11 (*in Chinese*)
[20] Behbahani S, Nasrabadi A M 2009 Application of SOM neural network in clustering *Journal of Biomedical Science & Engineering* **2**(8) 637-43
[21] Ghaseminezhad M H, Karami A 2011 A novel self-organizing map (SOM) neural network for discrete groups of data clustering *Applied Soft Computing Journal* **11**(4) 3771-8
[22] Specht D F 1990 Probabilistic neural networks *Neural Networks* **3**(1) 333-45
[23] Zhao L T, Chai T Y, Diao X K, Yuan D C 2012 Multi-class classification with one-against-one using probabilistic extreme learning machine *Lecture Notes in Computer Science* **7368** 10-9
[24] Yagiz S, Sezer E A, Gokceoglu C 2012 Artificial neural networks and nonlinear regression techniques to assess the influence of slake durability cycles on the prediction of uniaxial compressive strength and modulus of elasticity for carbonate rocks *International Journal for Numerical and Analytical Methods in Geomechanics* **36**(14) 1636-50

Authors

Yan Sun, born in 1990, Shuguang, Shandong Province, P.R. China

Current position, grades: Ph.D Candidate of School of Traffic and Transportation, Beijing Jiaotong University.
University studies: majored in Traffic and Transportation, and received his Bachelor Degree in Engineering in 2013 at School of Traffic and Transportation, Beijing Jiaotong University.
Scientific interest: intermodal transport planning and management.
Publications: two articles as the first author, including one journal article in Journal of Industrial Engineering and Management (2014 Vol.7 No.2) and one conference article in VMEIT 2014.

Maoxiang Lang, born in 1969, Gaotang, Shandong Province, P.R. China

Current position, grades: professor and Ph.D advisor at School of Traffic and Transportation, Beijing Jiaotong University.
University studies: He received his Bachelor Degree in Engineering in 1991 at Shanghai Tiedao University, and then received his Master and Ph.D Degree in 1994 and 2002, respectively, at Beijing Jiaotong University.
Scientific interest: transportation and logistics management, transportation marketing management and modern railway freight technology and management.
Publications: He has published more than 60 articles.

Danzhu Wang, born in 1985, Qinhuangdao, Heibei Province, P.R. China

Current position, grades: Ph.D Candidate of School of Traffic and Transportation, Beijing Jiaotong University.
University studies: Bachelor and Master Degree in Engineering in 2007 and 2010, respectively, at School of Traffic and Transportation, Beijing Jiaotong University
Scientific interest: design of railway freight/logistics service productions.
Publications: 5 articles.