Evaluating the Ecological Sustainable Transportation System with An Application of Radial Basis Function Neural Network

Yan Zhuang¹, Chunjiao Dong¹*, Jianpei Qian¹, Shengyou Wang¹, Song Xue¹

¹Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, Beijing 100044, China

*Email: cjdong@bjtu.edu.cn

Abstract. The ecological and sustainable development of urban transportation system is critical to improving the overall quality of life and achieving the goals of climate protection and sustainable development. The study focused on factors from level of social and economic development, the quality of transport service and urban ecological environment to develop a comprehensive assessment indicator system. A novel method for evaluating the ecological sustainable transportation system based on the radial basis function neural network (RBFNN) was proposed. Results of comparative experiments between RBFNN and the conventional BP neural network (BPNN) showed that the accuracy of RBFNN was 8.3% higher than that of BPNN while the training time was 27.2s lesser and the Root Mean Square Error (RMSE) was 0.15 smaller. In the case of Shenzhen, China, the proposed model gave a reasonable evaluation, which implied that RBFNN brought forward a new perspective for further research.

Keywords: Ecological sustainable transportation system; Radial basis function; Neural network; Assessment indicator system; Evaluation model

1. Introduction
Sustainable development is of great strategic significance for the development of human society. As a crucial part of the national economy, the transportation industry is an energy-intensive industry and needs to go further for ecological and sustainable development. There has been a trend in exploring different methods to evaluate the ecological and sustainable urban transportation development system. The main popular evaluation methods used are as follows: [1] applied the data envelopment analysis (DEA) to assess the aggregated efficiency of resource use and environment improvement. Simulation-based optimization (SBO) is incorporated to seek the evaluation and optimization of the sustainable transportation system [8]. Xu and Song [9] proposed a comprehensive evaluation method of sustainable transportation with entropy method. Fuzzy logic is adopted to evaluate the performance of transport sustainability [6]. Egbue [2] found a multimetric index to access the adoption of sustainable transportation by combining demographic determinants as well as behavioral and attitudinal measures. Jia and Zhang [5] studied the evaluation of the urban low-carbon and ecological transportation system by using the gray correlation model. The traditional
methods could arise a lot of disadvantages because of the susceptibility of human factor. It is mainly manifested in the unintentional exaggeration or reduction of the effect of certain indicators, so the evaluation result cannot truly reflect the actual situation of the object being evaluated. The methods mentioned were proved to be either subjective and fuzzy or slow in convergence speed and easy to fall into the local optimal solution with complex coding. Multilevel neural network for the evaluation of the sustainable development of urban transportation can reduce error in the assessment and thus is considered to be an important direction of the development of the evaluation method. It trains neural networks by collecting a mass of samples to assess the ecological and sustainable development of urban transportation system as a rule [7]. However, since all training samples constitute the hidden layer neurons directly, the larger the number of training samples, the more complex the neural network structure will be [4]. The BP neural network has a long running time because each adjustment parameter has the same influence on the output result and needs to be propagated back according to the error [3]. In order to shorten the running time and simplify the problem of the complex structure of the neural network due to the large training samples, this paper applied the radial basis neural network (RBFNN) to the evaluation model.

2. Assessment indicators of ecological sustainable transportation System
Assessment of ecological sustainable transportation system is not merely putting the ecological and sustainable indicators into the traditional evaluation system of urban transportation, but a comprehensive assessment aimed to reflect the connotation of the ecological sustainable transportation development, such as accessibility, social justice and so on. When determining the assessment indicator system and evaluation method, principles of systematization, scientificity, operability and practicability ought to be followed. In this context, this paper divides the assessment indicator system of ecological sustainable transportation system into three layers (Figure 1). The first layer is the overall goal of the ecological sustainable transportation system assessment, and the second layer includes three subsystems consisting of corresponding sub-indicators from the level of social and economic development, the urban ecological environment and the quality of transportation service as the third layer. The level of social and economic development mainly reflects the supporting role of transportation plays in social economy; The quality of transportation service mainly reflects the serviceability, fairness and universality of transportation to the whole society. The urban ecological environment mainly reflects the impact of transportation industry on the natural ecological environment.

Figure 1. Assessment indicators of ecological sustainable transportation system

3. Evaluation methods and model

3.1. Evaluation methods
For the individual sub-indicators interacting with each other in each subsystem, a radial basis function (RBF) neural network model is adopted to obtain their weights through sample training. As to the independent subsystems in the assessment system, neural network models are not suitable to adopt due to the small sample size. In order to minimize the effects of inadequate training data samples, the weights of different subsystems are obtained by the analytic hierarchy process (AHP) instead. They were achieved by constructing comparative judgment matrices between subsystems and sub-indicators integrating sophisticated suggestions of experts and literature. In this way, the updated weight of each indicator in the assessment system can be determined by weighted multiplication. Finally, the composite index reflecting the development level of ecological and sustainable transportation can be obtained.

### 3.2. Evaluation model

Radial basis function is a non-negative real value function whose radial symmetric value only depends on the distance from the center point. Supposed \( \mu_i \) is the gaussian center of the \( i^{th} \) node in the hidden layer and \( \sigma_i \) is the extension constant for the \( i^{th} \) node, then:

\[
\phi(\|x_i - \mu_i\|) = \exp\left(-\frac{\|x_i - \mu_i\|^2}{2\sigma_i^2}\right)
\]

The basic idea of the radial basis function neural network is that by changing the transformation function in the hidden layer into the radial basis function, the hidden layer can transform the input vector and transform the input data from low-dimensional space to high-dimensional linear separable. The smaller the distance between the input vector and the center point \( x_i \), the larger the output of the network, and the final output is:

\[
y_j = \sum_{i=1}^{S} o_{ij} \phi(\|x_i - \mu_i\|), j = 1, 2, \ldots, R
\]

In this paper, the generalized RBF neural network modeling mainly involves three kinds of parameters: the basis function center and extension constant, and the weight of the output node. Suppose the input space with \( R \) dimensions have \( X_n \) \((n = 1, 2, 3, \ldots, N)\) input samples. The specific algorithm steps are as follows:

1. Initialization. Select \( S^i \) different vectors as the initial clustering center \( q_i(0) (i = 1, 2, 3, \ldots, S^i) \), that is, \( S^i \) is the number of hidden nodes.
2. Calculate the Euclidean distance between each sample point in the input space and the center point of the cluster \( X_n - \mu_i(s) \) \((n = 1, 2, 3, \ldots, N)\), where \( \mu_i(s) \) represents the center of the \( i^{th} \) iteration.
3. Similarity matching. Let \( i^* \) represent the subscript of the winning hidden node, and determine the classification \( i^*(X_n) \) of each input sample \( X_n \) according to its minimum Euclidean distance from the clustering center, that is when \( i^*(X_n) = \min_i \|X_n - \mu_i(s)\| \), \( X_n \) is classified as class \( i^* \), consequently divide the whole sample into \( S \) subsets \( U_1(n), U_2(n), \ldots, U_S(n) \). Each subset constitutes a clustering domain typically represented by the clustering center.
4. Apply competitive learning rules to adjust and update all clustering centers.
\[ \mu_i(s+1) = \begin{cases} 
\mu_i(s) + \eta \left[ X_i - \mu_i(s) \right] & i = i^* \\
\mu_i(s) & \text{otherwise} 
\end{cases} \]

Add 1 to the value of \( s \) and turn to step 2. Repeat the process until \( |\mu_i(s+1) - \mu_i(s)| < \epsilon \).

(5) Determine the expansion coefficient. After determination of the center \( \mu_i \) of each cluster, the expansion constant \( n \) of the corresponding radial basis function \( \sigma_i = \frac{d_{max}}{\sqrt{2 \pi}} \) can be determined according to the distance between the centers, where, \( d_{max} \) is the maximum distance between the selected cluster centers.

(6) Output weights. The pseudo-inverse matrix method is used to calculate the weights between the hidden layer and the output layer. Let's define the matrix \( B = (b_{ni})_{R \times N} \), where, \( b_{ni} = \exp \left( -\frac{\|X_i - q_{ni}\|^2}{2\sigma_i^2} \right) \) \((r = 1, 2, 3, \cdots R; n = 1, 2, 3, \cdots N)\). The weight matrix \( \omega = (\omega_{ni})_{N \times I} \) of each node in the output layer is calculated as \( \omega = B^* T \), where \( B^* \) is the pseudo-inverse matrix of matrix \( B \), and \( T \) is the output expectation matrix in the training data set \( T = (t_i)_{N \times I} \).

4. Case Study

4.1. Data and samples
In this study, data during 2011 and 2018 is collected from Municipal Bureau of Ecology and Environment, Shenzhen Government Online, Municipal Bureau of Urban Management and Comprehensive Law Enforcement and other official websites of Shenzhen. The evaluation results are divided into five levels (V = {Ⅰ, Ⅱ, Ⅲ, Ⅳ, Ⅴ}) and the corresponding theoretical outputs are 1,2,3,4,5. The level of ecological sustainable transportation development is determined by the level of each indicator. When all sub-indicators are at the same level, the level of ecological sustainable transportation system belongs to the level as well. 100 samples were generated randomly of different levels by changing the seed of random function irregularly.80 groups of sample data were used as the training set of radial basis function neural network, while 20 groups of data were used as the test set for comparison and verification.

4.2. Establishment, training and verification of RBFNN model
RBF neural network design function newrb (), simulation function sim () and inverse function pinv () in MATLAB toolbox were utilized to establish a radial basis function neural network model. In order to demonstrate the applicability of RBF neural network to the evaluation of ecological sustainable transportation system, a comparative evaluation experiment was conducted between RBFNN model and traditional BPNN model. Taking the second level of development as an example, 20 test samples were input into the established RBFNN model and BPNN model respectively to obtain the images of the predicted value and the expected output value, as shown in Figure 2.
Figure 2. Comparison between the predicted output and the expected output of RBFNN

( Accuracy of RBFNN=95%, RMSE_{RBF}=0.28 ; Accuracy of BPNN=85%, RMSE_{BPNN}=0.43 )

Due to the contingency of a single experiment, this paper repeated 10 training experiments on test samples of different levels to obtain 10 result models, and recorded the accuracy of each model. Results are shown in Figure 3.

Figure 3. The predicted results of 10 repetitions at different levels in RBFNN (Average accuracy=87%)

Figure 4. Comparison in prediction accuracy

Figure 5. Comparison in run time

Table 1. The prediction accuracy of repeated experiments

|          | RBFNN | BPNN | Difference |
|----------|-------|------|------------|
| Accuracy (%) | 86.5  | 78.2 | 8.3        |
| Run time (s)  | 5.1   | 32.3 | 27.2       |

It can be concluded from Figure 4, Figure 5 and Table 1 that RBF neural network model has its unique advantages in accuracy, running time and stability. BPNN is much slower in operation speed since it has to be trained according to the error backpropagation algorithm. Therefore, it is demonstrated that the RBF neural network model constructed in this paper has high reliability and fitting ability for sample data.
4.3. Results and discussion

Collected data was entered into the RBF neural network model to obtain the weight of each sub-indicator at first. Weights of three subsystems were calculated to be 0.21, 0.38 and 0.41 respectively by AHP. Then the updated weights of indicators can be calculated as shown in the following table (Table 2).

Table 2. The weight of indicator of ecological sustainable transportation system

| Sub-Indicator | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | D11 | D12 |
|---------------|----|----|----|----|----|----|----|----|----|-----|-----|-----|
| Weight in RBFNN | 0.41 | 0.59 | 0.14 | 0.16 | 0.21 | 0.26 | 0.23 | 0.19 | 0.17 | 0.15 | 0.23 | 0.26 |
| Updated weight | 0.08 | 0.12 | 0.053 | 0.06 | 0.08 | 0.099 | 0.08 | 0.07 | 0.07 | 0.06 | 0.09 | 0.10 |

Therefore, the development level of ecological and sustainable transportation in Shenzhen over the years can be calculated as shown in the following table:

Table 3. Development of ecological sustainable transportation system in Shenzhen

| Year | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|------|------|------|------|------|------|------|------|------|
| Composite Index | 2.29 | 2.99 | 3.03 | 3.57 | 3.87 | 3.95 | 4.06 | 4.17 |
| Level | II | II | III | III | III | III | IV | IV |

Figure 6. Development of ecological sustainable transportation system in Shenzhen.

As can be seen from Table 3 and Figure 6, the index of ecological sustainable transportation system in Shenzhen maintained a stable upward trend from 2011 to 2018 and a fast growth in 2012 and 2014. Among the three subsystems, the urban social and economic development subsystem shows a declining trend, while the urban ecological environment subsystem and the traffic service quality subsystem show a rising trend year by year. It indicates that in recent years, the development of ecological sustainable transportation of Shenzhen runs well, which further implies the social and economic development continues to play a supporting role in the economy, the quality of transportation service is constantly improving, and the urban ecological environment is better improved.
4.4. Suggestions
Since the 26th Summer Universiade in 2011, Shenzhen has seized the opportunity to accelerate the demonstration and promotion of new energy vehicles, paying attention to the refined design of traffic facilities, and comprehensively improving the traffic environment. However, we still need to note that as good as the evaluation of ecological sustainable transportation system in recent years looks, it actually just meets the standard of level Ⅰ and still lags behind the level Ⅱ. Moreover, urban expansion, population suburbanization and the previous unreasonable planning of road traffic system and land use all aggravate the phenomena of ‘separation of workplace and residence’, making commuting time longer and traffic jam worse during rush hours.

Given the existing problems of Shenzhen’s ecological sustainable transportation system, this paper puts forward the following suggestions: 1) Keep intensifying investments in public transport to guarantee its priority status; Optimize the bus operation network and strengthen the traffic connection between east and west area to highlight social equity; 2) In the renewal of old towns and the movement of new towns, attention should be paid to the reasonable planning of urban land and balanced spatial allocation of basic public goods such as educational and medical facilities. 3) Upgrade and reform the existing road traffic system, and enhance cooperation between different traffic modes to solve the "last kilometer problem" of connection with public transport. 4) Draw on advanced traffic design and management experience at home and abroad like bringing in ‘the smart luminous zebra crossing’ to improve road traffic safety.

5. Conclusions
The paper chose corresponding indicators from social economy, service quality of transportation and the ecological environment at three different levels to build up a comprehensive indicator system for ecological sustainable assessment of urban transportation system. Furthermore, a radial basis function neural network (RBFNN) was established as foundation of the evaluation model. Empirical study indicated that the novel approach developed in this study outperformed the traditional BP neural network in abilities of approximation, classification and learning speed. Finally, the development of ecological sustainable transportation system in Shenzhen over the years is evaluated, and corresponding suggestions for improvement are put forward. Properties of RBF neutral network might perform better with a more rigorous and objective approach in the future. The robust RBFNN did pave a new way to study the ecological and sustainable development of transportation system.

6. References
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