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Integrated Intersection Evaluation Method Based on BP Neural Network

Yan Zhang [a], Yanxin Zhang [b]

School of Electronic and Information Engineering, Beijing Jiao Tong University, Beijing 10044, China.

[a]16120279@bjtu.edu.cn, [b]yxzhang@bjtu.edu.cn

Abstract. With the development of the Wangjing regional economy, the number of cars in the region has increased. In order to allow inter-regional vehicles to pass with high efficiency, it is necessary to perform some efficient control at the boundary of the area. First, controlling the intersection of the entire transportation network is not effective and economical. Therefore, it is necessary to evaluate the boundary intersections so as to select the more important intersections on the regional boundaries for control.In this paper, the road network partition was first carried out. This paper mainly uses the basic properties of the traffic network to partition the road network.The boundary intersections are evaluated based on the repartitioning to select more important intersections for control at the regional boundaries.In this paper, we mainly use the three indicators of social network analysis method, system science analysis method, and traffic network characteristics method to evaluate the intersections, and use neural network training to get the weight of each indicator, so as to determine a comprehensive evaluation method. Feedback gate control based on fuzzy PID is applied to the traffic network based on the selected important intersection, thereby alleviating the congestion in the effective central city.

Keywords: Transportation network, Social Network Analysis busyness, Systematic scientific analysis, Traffic characteristics, Neural network.

1. Introduction

As the number of vehicles in the Wangjing area has increased, the probability of traffic jams and accidents has also gradually increased. Traffic jams are mainly due to irrational signal timing at intersections and limited capacity. In order to reduce the complexity of signal control between regions, it has become a mainstream trend to select important intersections at regional boundaries and control these intersections[1-9]. As a result, the throughput of the vehicles in the area is optimized. The previous major intersection studies were mainly divided into three categories. In the literature[10, 11], the degree of centrality in social network analysis was used to evaluate the importance of nodes. In the literature[12-14]was used the system science analysis method to evaluate the nodes, which are the node contraction method, the node deletion method, and the m-order neighbor node method to evaluate the nodes. The node contraction method is fast and can evaluate the importance of complex network nodes with high efficiency, but it does not combine the characteristics of traffic network, so it can not scientifically and effectively evaluate the importance of intersections in traffic networks. The m-order neighbor node fully considers the influence of the neighbor node on this node. The criterion of node deletion method is the degree of network change after node deletion. In the literature[15-18]evaluates the urban road network by adding traffic flow characteristics in the road network, such as: the popularity of the route, the speed of the trip, and the density of traffic, etc., to determine the importance of the intersection. At present, the method of using social network analysis method and system science method to evaluate nodes in complex networks has become more mature. Based on this, the attributes of traffic network are added and neural network is used to obtain a comprehensive evaluation index with higher credibility.

2. Important Assessment Methods

This paper mainly selects four indicators (centrality, node contraction method, busyness, congestion degree) from above three aspects to determine the importance of nodes in the transportation network.. The specific indicators are as follows:

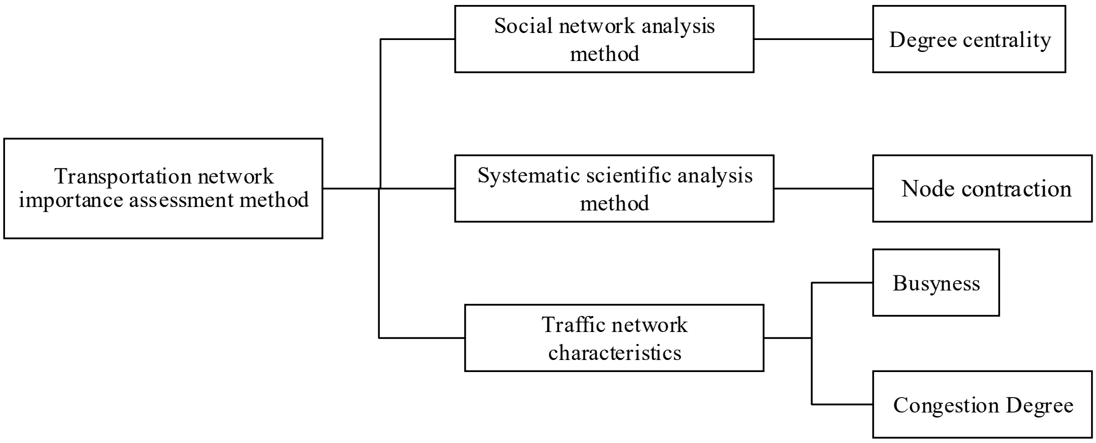

Fig.1 Evaluating indicator

2.1 Centrality

In the Social network analysis method, the degree of a node is the number of nodes adjacent to the node in a complex network, is defined as follows.

$$DC(i) = \frac{\sum a_{ij}}{n-1} = \frac{k_i}{n-1} \tag{1}$$

In the formula: a_{ij} is the element in the adjacency matrix of the network, $\sum a_{ij}$ is the number of connected nodes of node i, k_i is the degree of node i in the network, and n is the number of nodes in the complex network.

From the difination, we know that the greater the number of node neighbors is, the more important the nodes are. It can directly reflect the influence of nodes, which should be the most important characteristics in the complex network.

2.2 The Node Contraction Method

From Systematic scientific analysis, the node contraction method is to Shrink the node with the node to 1 node, that is, to generate one new node to replace nodes.

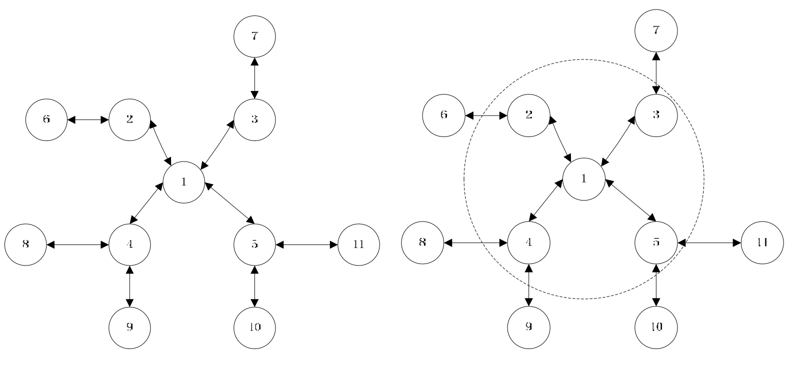

Fig.2 meshed network

For the degree of aggregation of network, it is defined as:

$$\partial[G]=\frac{1}{n\times l}=\frac{n-1}{\sum_{i\neq j}d_{ij}} \tag{2}$$

Where n is the number of nodes, l is the average path length, and d_{ij} is the shortest distance between nodes i and j.

The evaluation of the importance of the node v_i in the network G is mainly combined with the degree of aggregation before and after the contraction of the node v_i, and defined as:

$$IMC(v_i)=1-\frac{\partial[G]}{\partial[G*v_i]} \tag{3}$$

In the formula: $\partial[G]$ is the degree of aggregation of the network, and $\partial[G*v_i]$ is the degree of aggregation of the new network resulting from the fusion of node v_i with the surrounding k_i nodes. It is proved that nodes k_i are important nodes in a complex network, if the network has the highest degree of aggregation.

2.3 Traffic Network Characteristics

2.3.1 Busyness

The busyness is obtained from the traffic volume of the current road section and the saturated traffic volume of the road section and is defined as:

$$F_i=\frac{q_i}{c_i} \tag{4}$$

Where F_i is the busyness of the intersection, q_i is the traffic flow, and c_i is the saturation flow.

2.3.2 Congestion Degree

It is shown that the amount of fuel consumed by the same number of vehicles is different at different times even for a certain road segment. During periods of congestion, the vehicle consumes a large amount of fuel because of its start-up and braking. Although some road junctions in the urban traffic network are relatively busy, the intersections are not easy to be congested due to the large capacity of the roads. Therefore, this paper proposes to use fuel consumption as an evaluation index. In addition to the topological attributes of the road network and the busyness of intersections, a new indicator is added. In order to use a variety of factors to evaluate the intersection, we can scientifically and effectively judge the importance of the intersection in the road network. The degree of congestion at the intersection is based on the fuel consumption of the current intersection and the total fuel consumption of the area. The data in this paper is provided by the Intelligent Transportation Center, where fuel consumption is collected by the fuel consumption sensors. The degree of congestion is as follows:

$$Y_i=\frac{o_i}{O} \tag{5}$$

Where o_i is the fuel consumption at the intersection and O is the total fuel consumption of the area.

3. Comprehensive Evaluation Model

The nodal shrinkage method has the characteristics of being intuitive, effective, and faster, and has an ideal computing capability in a complex network. However, in the transportation network, it is obviously not enough to consider only the characteristics of the network topology. Therefore, traffic flow and fuel consumption are included in the assessment index. The traffic flow can be used to evaluate the busyness of the road section. The fuel consumption is used to evaluate the number of vehicles parking in a certain road section and the degree of congestion on the road section. The centrality determines the influence of the intersection through the number of intersections that are connected to the intersection. As a result, a comprehensive assessment indicator is produced as follows:

$$I\left(v_i\right)=\alpha IMC\left(v_i\right)+\beta F\left(v_i\right)+\mu Y\left(v_i\right)+\delta IMD\left(v_i\right) \tag{6}$$

In the formula: $I(v_i)$ is the degree of importance of the nodes in the transportation network, $IMC(v_i)$ is the degree of importance obtained by the node contraction method, $IMD\left(v_i\right)$ is the degree of importance obtained by using the degree of the node, $F(v_i)$ is the busy degree, and $Y(v_i)$ is the degree of congestion. $\alpha, \beta, \mu, \delta$ is the weight of different assessment indicators, which can be trained by neural networks.

In order to determine the weights of various assessment indicators in the transportation network, neural network technology is used here, which needs known sample learning and expert experience[19]. The following figure is a basic BP (Back-Propagation) neuron model, which has four inputs as i,one-output as j, connected by corresponding weights and transfer functions, the output of the network is:

$$Y = f\left(\omega X + \theta\right) \tag{7}$$

Where x_1 is the degree of each node, x_2 is the importance of each node obtained by the node contraction method, x_3 is the busyness of the intersection, and x_4 is the congestion degree of the intersection. This article mainly uses the busyness of intersections in different time periods to train the weight value closest to the expected value.

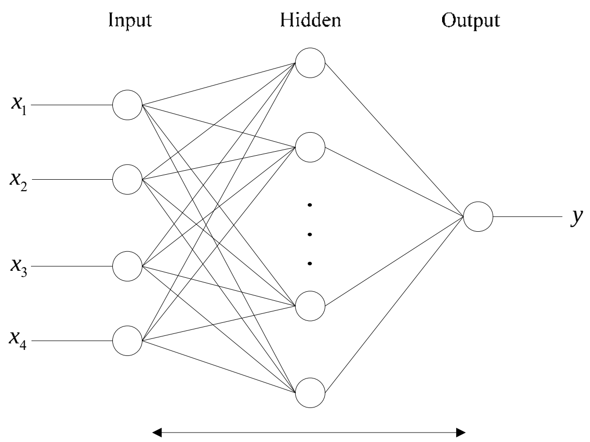

Fig.3 back propagation neural network

The input from the hidden layer is:

$$Net_k^1 = \sum_{i=1}^{m} w_{ki}^1 x_i + \theta_k \tag{8}$$

Where w_{ki}^1 is the weight of the first layer, and x_i is the value of the i input of the neural network, and the number of elements in the input layer is m, θ_k is the threshold of the hidden layer. Hidden layer output:

$$o_k = f\left(Net_k^1\right) = f\left(\sum_{i=1}^{m} w_{ki}^1 x_i + \theta_k\right) \tag{9}$$

In the formula: o_k is the output of the hidden layer and f is the transfer function.

Transfer function (S-function):

$$f(x) = \frac{1}{1+e^{-x}} \tag{10}$$

Output layer input:

$$Net_o^2 = \sum_{k=1}^{p} w_{ok}^2 o_k + \theta_o \tag{11}$$

In the formula: o_k is the output of the hidden layer, w_{ok}^2 is the second layer weight, p is the number of neurons in the hidden layer, and θ_o is the output layer threshold.

Output layer output:

$$y_o = f\left(Net_o^2\right) = f\left(\sum_{k=1}^{p} w_{ok}^2 o_k + \theta_o\right) \tag{12}$$

Hidden layer to output layer weight correction:

$$\Delta w_{ok}^2 = \eta\left(\widehat{y_o} - y_o\right) y_o \left(1 - y_o\right) o_k \tag{13}$$

The correction of the weight of the input layer to the hidden layer:

$$\Delta \omega_{ki}^1 = -\eta \sum_{i=1}^{n} \left[\left(\widehat{y_o} - y_o\right) y_o \omega_{ok}^2\right] o_k \left(1 - o_k\right) x_i \tag{14}$$

By using the BP neural network method, input data including the node contraction method, busy degree, congestion degree, and degree-centrality data into the NN for training, and obtain the weight matrix from the input layer to the hidden layer, the hidden layer to the output layer. From the weight matrix, we can get the weight of each index.

4. Experimental Analysis

4.1 Establishment of Beijing Wangjing Regional Road Network Model

The Beijing Wangjing area is located in the northeast of Beijing. Large traffic volume at intersections and limited traffic capacity can easily cause traffic congestion. Therefore, it is necessary to screen out important nodes through the method of importance evaluation, allocate more traffic resources to these important nodes and choose the optimal signal timing plan, so as to ensure the smooth operation of traffic at this these intersections. This experiment selected some areas of Wangjing(longitude: 116.47014141—116.48400307, latitude:39.9877436—39.99875571:). As shown below.

Fig.4 Selected areas under the Google map

4.2 Simulation Data Acquisition

Fig.5 Wangjing region

First, we use the Gaode map to find the selected area, and then number the intersections and sections in the selected Wangjing area (see Figure 15). There are 15 intersections and 23 sections in this area. Based on the longitude and latitude of the Wangjing area, the floating car data in Beijing were screened, and then the traffic data, fuel consumption, steering angle, etc. of the floating cars in the Wangjing area were processed. Then the length of each road section was measured by the distance measurement function of the Baidu map. The specific data is shown in the table below.

Table 1. Road length

Road	Length	Road	Length	Road	Length
L1	215	L9	280	L17	355
L2	103	L10	350	L18	360
L3	160	L11	250	L19	213
L4	210	L12	255	L20	280
L5	255	L13	250	L21	295
L6	360	L14	200	L22	308
L7	305	L15	280	L23	295
L8	550	L16	210		

The data used in this paper is the Beijing taxi data provided by the Intelligent Traffic Big Data Center. Through the latitude and longitude of the study area, the floating car data of the selected area are screened out in the data of the total floating car, such as vehicle identification, instantaneous fuel consumption, etc. The main data is shown in the table below.

Table 2. Floating car data

Intersection	Number	Fuel	Intersection	Number	Fuel
V1	3796	900953	V9	506	132910
V2	1773	470000	V10	3289	815690
V3	1549	357421	V11	420	114091
V4	837	219822	V12	1664	510998
V5	3565	884747	V13	2450	600218
V6	2413	558561	V14	1550	412694
V7	2622	652883	V15	1276	370365
V8	335	91458			

4.3 Importance Evaluation Method Simulation

Using the node contraction method to assess the importance of the intersection in the Wangjing area:

1) Enter the initial distance matrix and calculate the shortest distance between the nodes.

2) The pre-shrinkage nodal agglomeration is calculated by the formula.

3) In the following figure, node 1 is shrunked. The degree of condensation after shrinkage is calculated, and the importance of the node is obtained by the degree of aggregation before and after the contraction of the node.

4) Calculate the aggregation of each node in turn.Get the importance of all nodes and sort them.

The schematic diagram of the node contraction method applied in the Wangjing area is as follows:

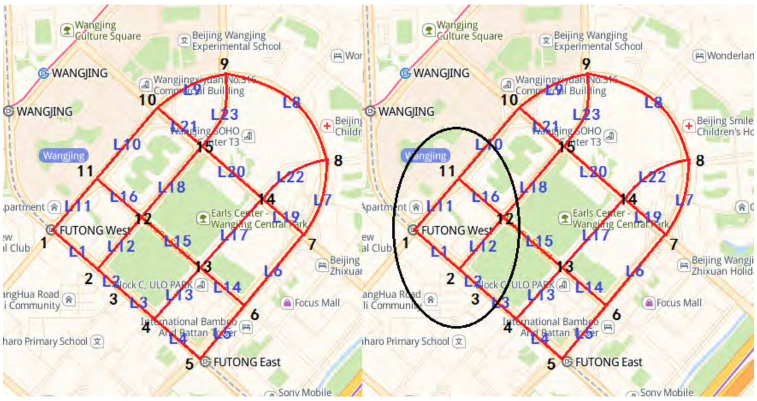

Fig.6 Node contraction

Using the degree of business, degree of centrality, node contraction method and the fuel consumption of the vehicles to get the importance of the following table.

Table 3. The importance of the nodes obtained by the various factors

Intersection	Busyness	Congestion	degree	IMC	Intersection	Busyness	Congetion	degree	IMC
V1	0.135	0.127	0.143	0.561	V9	0.018	0.018	0.214	0.626
V2	0.063	0.066	0.214	0.592	V10	0.117	0.115	0.214	0.614
V3	0.055	0.050	0.143	0.559	V11	0.015	0.016	0.214	0.603
V4	0.030	0.031	0.214	0.592	V12	0.059	0.072	0.286	0.604
V5	0.127	0.125	0.143	0.561	V13	0.087	0.085	0.286	0.605
V6	0.086	0.079	0.214	0.605	V14	0.055	0.058	0.286	0.647
V7	0.093	0.092	0.214	0.616	V15	0.045	0.052	0.286	0.643
V8	0.012	0.013	0.214	0.524					

Judging by the degree of congestion, V1 intersection is the most important intersection. The use of node contraction method to determine the V14 intersection as the most important intersection. When the centrality of degree is used, it is determined that V12, V13, V14, and V15 are the most important intersections. Different evaluation factors have got different results. Therefore, we need to obtain the weights of different evaluation factors through neural network training, taking into account the influence of various factors on the intersections, and thus scientifically and effectively determine the importance of intersections.

4.4 Neural Network Simulation

Experiments have shown that when the number of neurons in the hidden layer is 8, the convergence is better at this time and the calculation is smaller.This article selected some samples to be trained through a neural network. The weights obtained from the BP neural network are shown in the following table.

Table 4. Weight coefficient table of four evaluation indexes of traffic network

Hidden layer unit	Input layer unit				Output layer unit
	1	2	3	4	
V1	-1.459	-0.999	-0.960	1.260	-0.142
V2	-0.258	1.504	-1.515	0.971	-0.145
V3	-1.439	-1.067	1.032	1.135	0.208
V4	0.887	1.664	-0.652	1.178	-0.278
V5	-0.830	-1.768	1.107	-0.670	0.323
V6	2.058	-0.678	-0.512	0.874	1.352
V7	1.062	-2.008	0.608	0.354	-0.616
V8	0.323	0.649	-2.206	0.167	0.353

The weights of the input layer-hidden layer and the hidden layer-output layer can be obtained through the neural network. However, we ultimately need to obtain the weight relationship of degree-centrality, busyness, fuel consumption, and node contraction method. Therefore, the following indicators are needed.

Relevant significant coefficient

$$r_{io}^{T}=\sum_{k}\omega_{ki}\left(1-e^{-x}\right)/\left(1+e^{-x}\right) \tag{15}$$

$$x=\omega_{jk} \tag{16}$$

Correlation coefficient

$$R_{io}=\left|\left(1-e^{-y}\right)/\left(1+e^{-y}\right)\right| \tag{17}$$

$$y=r_{io} \tag{18}$$

Absolute influence coefficient

$$S_{io}=R_{io}\Big/\sum_{i=1}^{m}R_{io} \tag{19}$$

In the formula: w_{ki} is the weight matrix between the input layer and the hidden layer, w_{jk} is the weight matrix between the hidden layer and the output layer, m is the number of input layer nodes, n is the number of output layer nodes, p is the hidden layer node number.

Calculated by MATLAB: $\alpha = 0.6570, \beta = 0.0973, \mu = 0.1131, \delta = 0.0503$

The order of the importance of the final node is shown in the following table.

Table 5. Node importance ranking

Intersection	Importance	Rank	Intersection	Importance	Rank
V1	0.306	13	V9	0.540	6
V2	0.406	10	V10	0.698	3
V3	0.098	15	V11	0.363	11
V4	0.320	12	V12	0.526	8
V5	0.299	14	V13	0.574	5
V6	0.538	7	V14	0.819	1
V7	0.654	4	V15	0.777	2
V8	0.514	9			

From the above table, it can be seen that the major intersections V14, V15, and V10 are evaluated using the comprehensive evaluation index, and the less important intersections are V1, V5, and V3. Using comprehensive assessment indicators, the impact of each factor on the intersection can be analyzed more comprehensively and clearly, making the assessment result more reasonable and credible.

5. Conclusion

This paper takes the typical region of Wangjing in Chaoyang District of Beijing as a model. With a view to allocate more traffic resources to the more important intersections in the actual road network in order to avoid crossroads, it is more conducive to choose the most important intersections. Firstly, the limitations of some traditional methods for assessing the importance of nodes in complex networks are analyzed. Secondly, a comprehensive index for assessing the importance of intersections was established by increasing the busyness, the degree of congestion obtained from fuel consumption, the degree of centrality, node contraction method. And using BP neural network training to get the weight of each factor in this comprehensive evaluation index, from the perspective of mathematical analysis of the importance of the intersection. The redistribution of road resources at the important intersections selected this time can effectively reduce the pressure at the intersections.

Acknowledgments

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