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Research Article

Rural Road Network Planning Based on 5G and Traffic Big Data

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In order to adapt to the healthy development of China's road network and the prosperity of the rural economy, rural roads are facing the need to continue to promote the construction of roads that reach deeper nodes. It is urgent to conduct in-depth and systematic research on the planning methods of China's rural networked roads. A road network model oriented to rural road network planning is proposed. First, the traffic demand is predicted, and then remote sensing technology and computer technology are used to evaluate the technical performance of the rural road network. The experimental results show that the comprehensive evaluation index value is 0.8 by combining the weight of each index, and the planning scheme is comprehensively evaluated. The evaluation results show that the program better supports the local social and economic development.

1. Introduction

Rural roads are an important part of the road network. Rural roads are like capillaries, spreading all over the province [1]. Realizing that road transportation finally reaches the most terminal road, it forms the entire road transportation network together with national and provincial highways and other arterial roads, thus ensuring the supply of raw materials and the circulation of commodities. It provides conditions for farmers to approach the market, reach the market, and improve their own development capabilities, as shown in Figure 1 [2]. How to build a new rural road? The first task is to plan the new rural roads. Planning is the focus of the preliminary work of all construction projects. Without systematic and comprehensive planning, there can be no good construction results [3]. On the one hand, China has formally proposed a major strategic adjustment of the working ideas and investment structure of rural road construction. It is the first large-scale rural road construction in the history of transportation development. Objectively, it is necessary to formulate a comprehensive and long-term development plan for rural roads; on the other hand, active and effective exploration in the development planning of rural roads and continuous improvement of the overall functions of the road transportation network are also an important link in realizing the leap-forward development of transportation [4].

2. Literature Review

After the new century, we have ushered in a new era of geospatial data acquisition [5]. Liu et al. found that compared with low resolution and medium resolution remote sensing images, high-resolution images have more abundant feature information, spatial structure, and geometric texture features, which can assist us in more effective feature recognition and real-time data update [6]. Mavromoustakis et al. found that high-resolution image data have gradually become the main data source for GIS data update, target extraction, target recognition, digital mapping, and other technologies [7]. Therefore, an important research direction in the field of remote sensing discovery is how to extract objects of interest quickly and accurately from high resolution remote sensing images. Among many information that people pay attention to, the road as the basic geographic data and the important feature target is an important part of the GIS database. For a long time, the extraction of road feature information has been a hot research topic, and its

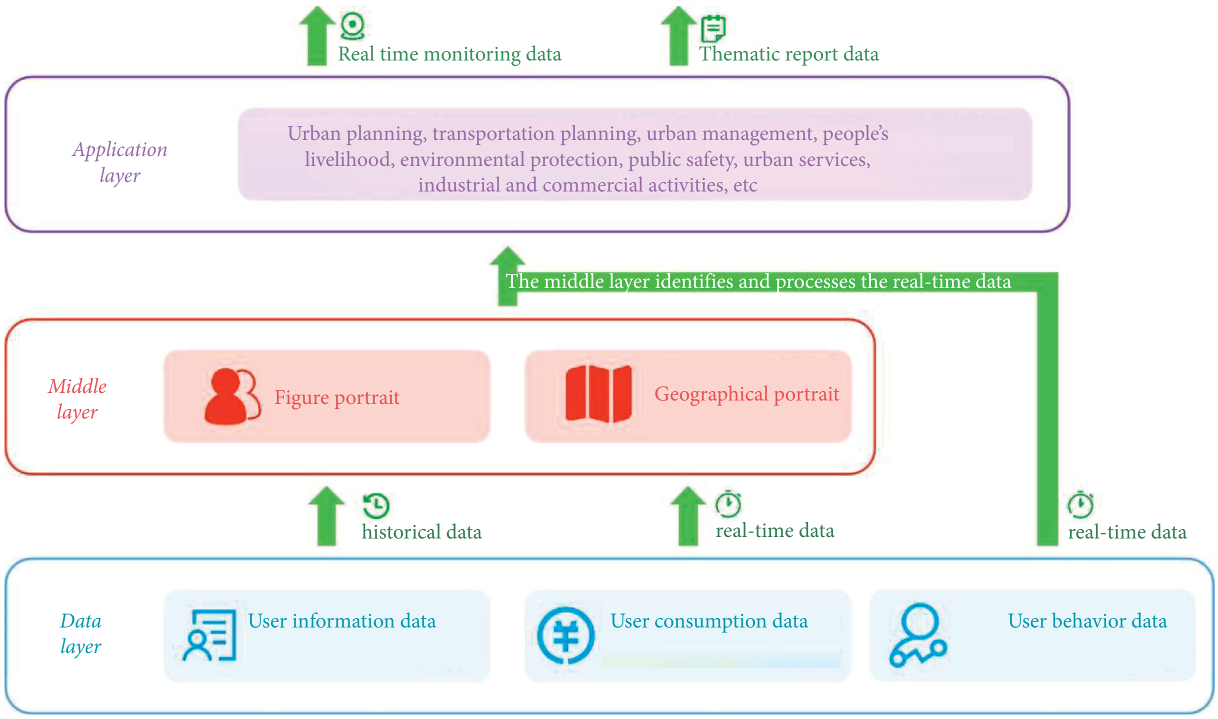

Figure 1: Flowchart of data operation.

importance to urban planning and construction, urban navigation, traffic management, database update, etc., is particularly prominent [8]. Park et al. found that high-resolution remote sensing images contain a large amount of extremely rich feature information, and road targets are becoming more and more clear. It breaks the limitations of incomplete details and unclear boundaries caused by low- and medium-resolution images, and basically meets the requirements of GIS data for information accuracy [9]. However, Xu et al. found that due to the increase in resolution, the detailed features of the ground objects in the image are particularly prominent, and the road presents a more complex form of expression [10]. The main characteristics of roads in high-resolution images are as follows: different materials between road segments and different spectral characteristics presented, resulting in the phenomenon of "same objects with different spectrums;" in the urban background with complex target backgrounds, many nonroad area objects show spectral features very similar to roads, with the phenomenon of "same-spectrum foreign objects;" and the different widths of main and secondary roads; all of these have made road extraction more difficult. In addition, Tang et al. found that the occlusion of vehicles, trees, and building shadows also caused interference to the extraction of roads. Extracting road information from high-resolution remote sensing images is a hot and difficult point of current research, and many research results have been achieved. In rural areas where the target background is relatively simple, because the road has a single form of expression and the spectral difference with the background is large, it is less difficult to extract [11]. Chen found that various road extraction algorithms have more or less problems in the suburbs and urban areas with complex target backgrounds [12]. At present, Hou and Li found that the methods of extracting roads from high-resolution remote sensing images are mainly classified into classification-based methods and template matching-based methods. In the classification-based method, the main technologies involved are object-based image analysis (OBIA) and deep learning technology [13]. Meng et al. found that based on the OBIA classification for road extraction effect is largely dependent on the quality of the image segmentation results. As a preprocessing step, segmentation is also the most critical step. So far, there is no optimal segmentation algorithm to solve this problem [14]. Deep learning technology has been widely used in computer vision due to its powerful feature learning ability. Among them, a convolutional neural network (CNN) has been widely used in image classification and target detection since 2012. The use of CNN's image classification technology for road extraction has become a hot spot, and CNN can automatically perform feature learning from raw data. Liu et al. approached complex classification problems by learning a multilayer nonlinear network structure, searching for and discovering the internal structure and relationship of road targets from massive amounts of big data, which demonstrates the powerful ability to learn the essential characteristics of the dataset from the sample set. Although CNN has achieved some results in ground feature extraction, data input dimensions, network model optimization, and model parameter settings are relatively complicated, and there is no unified reference standard [15]. Because the results of road extraction by various methods are not satisfactory, the design of a new method for extracting roads quickly and accurately from high-resolution remote sensing images still has important scientific significance and practical value. Combining the advantages of OBIA-based CNN classification and template matching technology, a new template matching method that automatically generates templates is proposed to refine the road based on OBIA-based CNN classification rough extraction. The method strives to reduce the number of manual advances as much as possible, improves the degree of automation and extraction accuracy, and meets the needs of drawing output, as shown in Figure 2.

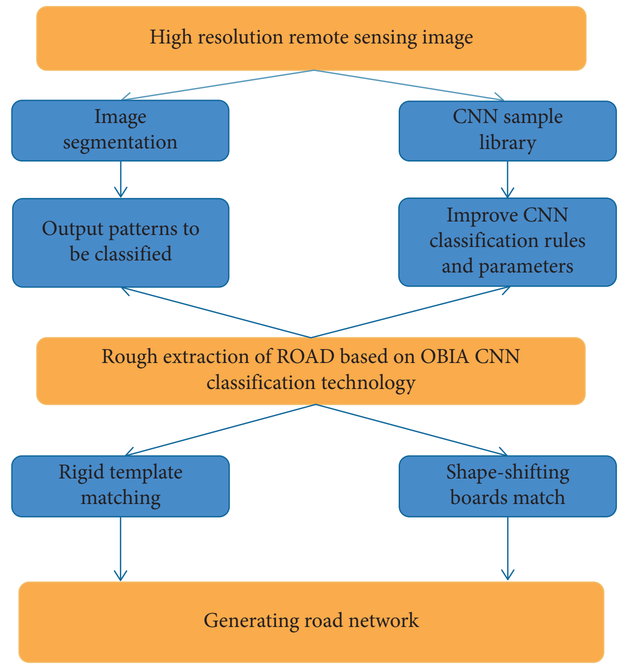

Figure 2: Flowchart of road extraction technology.

3. Method

Road networks at all levels are not isolated. They are an organic whole. If the road network is compared to the human body circulatory system, the national road network is the active vein, and the provincial network is the main blood vessel, and blood is transported to all parts of the body through the local road network as the capillaries. Only the coordinated development of the three can work together to complete the blood circulation of the human body and protect the health of life [16], as shown in Figure 3.

According to the analysis of the actual problems faced by rural road network planning, the theory required for rural road network planning should be planned based on the social and economic development in the background and based on the existing social traffic data. The framework diagram of the rural road network planning system is shown in Figure 4.

The scope of rural road network planning is very large. However, for a certain project in a certain area, the scope of influence is small, the amount of work is small, and the construction time is short. Therefore, the exponential smoothing method suitable for medium and short-term forecasts should be used when selecting the method. The quadratic exponential smoothing method is usually used in traffic planning, and the calculation formula is as follows:

$$\begin{cases} S_0 - S_0 - X_1 \\ S_1 - aX_t + (1-a)S_{t-1} \\ S_t^n = aX_t^1 + (1-a)S_t^n - 1 \\ a = \dfrac{1}{N} \end{cases}, \qquad (1)$$

In the above formula, X_t denotes the observation value at time t; X_1 denotes the observation value at the first time point; N denotes the number of samples; $S_t^{\prime}$ denotes the linear exponential smoothing value at time t; $S_t^{\prime\prime}$ denotes the second exponential smoothing value of time t; $S_0^{\prime}$ denotes the initial linear exponential smoothing value; $S_0^{\prime\prime}$denotes the initial quadratic exponential smoothing value; A denotes the smoothing factor, generally given by experience. Most of the values are between 0.01 and 0.3. Using the smoothed value to predict, the calculation formula is as follows:

$$\begin{cases} Y_{t+T} = a_t + b_t T \\ a_t = 2S_t - S_t^n \\ b_t = \dfrac{a}{1-a}\left(S_t - S_t^n\right) \end{cases}. \qquad (2)$$

In the above formula, T denotes the time t after time t; Y_{t+T} denotes the predicted value at time T after time t; $a_t.b_t$ denotes the calculation factor.

Elastic coefficient method is a comprehensive analysis method which combines qualitative and quantitative methods. The traffic growth rate is predicted according to the future growth of the national economy so as to predict future traffic generation. Therefore, by analyzing the change law of economic development in the planned area and the relationship between them and transportation, we can grasp the change law of transportation demand. When determining the elasticity coefficient, the traffic volume and traffic turnover volume in the planning area are generally used as traffic indicators to analyze with the GDP of the planning area [17]. The elasticity coefficient is defined as follows:

$$E = \frac{i_y}{i_x}. \qquad (3)$$

In the above formula, E denotes the elasticity coefficient; i_y denotes the annual traffic index change rate; i_x denotes the annual change rate of social and economic indicators.

The traffic index prediction formula is as follows:

$$Q_N = Q_0\left(1 + E \cdot i_x\right)^N. \qquad (4)$$

In the above formula, Q_N denotes the planning annual traffic index value; Q_0 denotes the base year traffic index

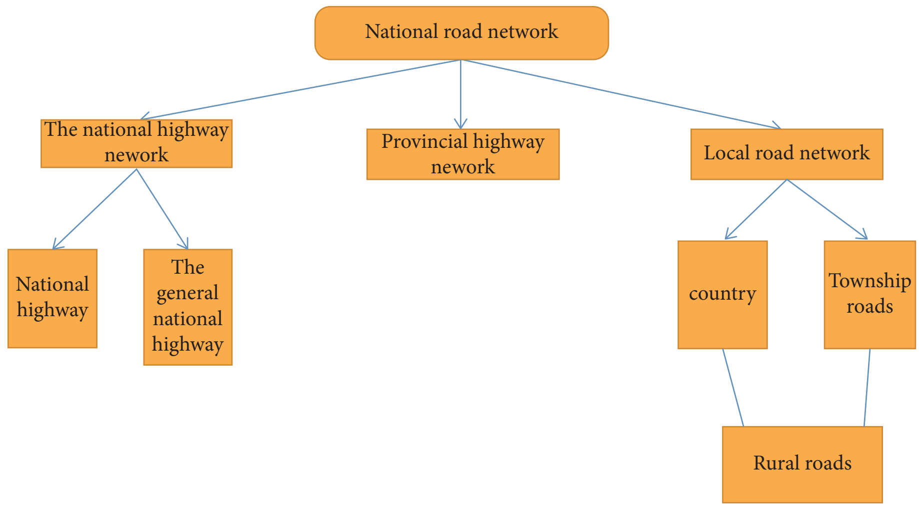

Figure 3: Classification of the national highway network according to administrative levels.

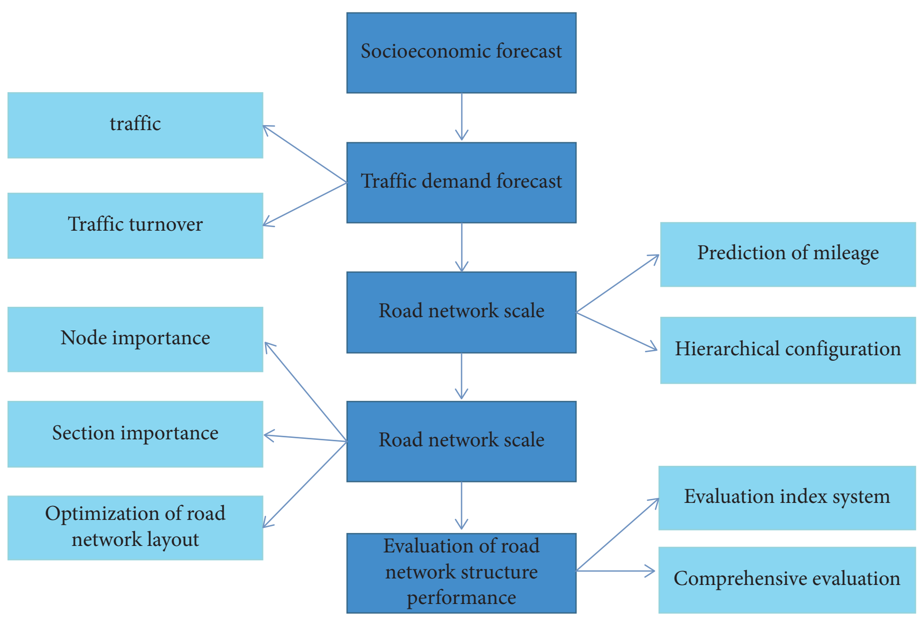

Figure 4: Framework diagram of rural road network planning system.

value; i_x' denotes the planning annual change rate of social and economic indicators.

The theoretical basis of the node connectivity method is network geometry, which mainly reflects the degree of connection between the road network and the nodes in the social economic network. This method considers the relationship between the area of the planned area, population, urban distribution, and other factors and the scale of the road network, and uses the connectivity value to reflect the impact of society, economy, and traffic on the scale of the road network. This method can reflect whether the road network is well connected to the nodes of the network and fully meet the requirements of the rural road network planning for the connectivity of the nodes in the road network. For the study of network geometry, the following models are established:

$$L = C \cdot \omega \cdot \sqrt{A \cdot N}. \tag{5}$$

In the above formula, L denotes the total highway mileage, kilometers; C denotes the road network connectivity; N denotes the number of nodes in the planning area; A denotes the planning area, square kilometers; ω denotes the road network deformation coefficient.

In the case of a certain planned area and node administrative division, the scale of the road network is mainly affected by the road network connectivity and the road network deformation coefficient. Each node in the planning area depends on the strength of the road interconnection, which is called the connectivity of the road network. The value of connectivity has a great influence on the total mileage. Therefore, starting from the natural geographical conditions of the planned area, it is necessary to select appropriate road network planning parameters and not blindly pursue the improvement of node connectivity. The following figure shows the layout of the road network and nodes when different specific values of connectivity are selected [18].

According to Table 1, it is concluded that when determining the value of connectivity, the strategic planning and positioning of the entire road network must be fully considered. When the requirements of the road network are high, the value of connectivity must be large, and vice versa. Therefore, the choice of connectivity should be specifically determined according to different planning areas and different planning goals. Table 2 shows the different connectivity values of different planned target road networks.

The road network deformation coefficient is also called the nonlinear coefficient, which is the ratio of the total mileage of the actual line between the nodes to the total mileage of the straight line. It is usually the road network deformation coefficient selected qualitatively according to the actual situation and planning objectives of the planning area. Generally speaking, for areas with more complex terrain conditions, the value of the road network deformation coefficient is roughly 1.30~1.65; for areas with better terrain conditions, the value is generally 1.10~1.30.

At present, the land coefficient method is the most commonly used method to predict the reasonable scale of the road network. The model believes that the reasonable length of the regional road network is related to the level of regional economic development, population, and land area. The calculation formula is as follows:

$$L = K \cdot \sqrt{A \cdot P}. \tag{6}$$

In the above formula, L denotes the total highway mileage, kilometers; P denotes the number of people in the planning area, ten thousand; A denotes the -planning area, square kilometers; K is the economic development level coefficient.

The coefficient K of the economic development level of the highway network is determined by the statistical regression analysis of the survey data of per capita GDP. After the reasonable scale of the highway network is determined, in accordance with the socioeconomic and highway development strategy, according to specifically related factors, the multiobjective planning theory is applied to optimize various hierarchical structure schemes to determine the highway network hierarchical structure as the basis for the highway planning layout. Under normal circumstances, the determination of the highway network hierarchy mainly considers three main aspects, namely, "the least funds for the construction of the road network," "the least travel time of the road network," and "the greatest traffic capacity of the road network." For other influencing factors, it can also be added or deleted to the influencing factor system based on actual conditions [19]. The optimization model of the highway network hierarchical structure is as follows:

$$f = \min\left[\left(n_1^+ + n_1^-\right)\left(n_2^+ + n_2^-\right)\left(n_3^+ + n_3^-\right)\right]. \tag{7}$$

Restrictions are as follows:

$$\sum_{j=3}^{4} A_j L_j - n_1^+ + n_1^- = I + I_n, \tag{8}$$

$$\sum_{j=3}^{4} C_j L_j - n_3^+ + n_3^- = Q_{NTF} | S_{NF}, \tag{9}$$

$$r_j \sum_{j=3}^{4} L_j < L_j < R_j \sum_{j=3}^{4} L_j, \tag{10}$$

$$\sum_{j=3}^{4} L_j = L_N. \tag{11}$$

Among them, n_j^+, n_j^- denote the deviation variable; L_j denotes the J-level highway planned mileage, kilometers; A_j denotes the J-level highway construction funds, ten thousand yuan/km; I, I_N denote the available funds for road construction and conversion costs of existing roads during the planning period, 10,000 yuan; Q_{NTF} denotes the planned annual road network traffic turnover, vehicle kilometers/year; C_j denotes the J-level highway capacity, vehicles/year; S_{NF} denotes the highway network planning service level, that is, the saturation of the planned road network; r_j, R_j denote the upper and lower limits of the change in the proportion of roads of level j ($j = 3, 4$).

The model starts from three aspects: the least funds for the construction of the road network, the least travel time of the road network, and the largest traffic capacity of the road network, taking increase or decrease in the proportion of each grade of the road in the road network as a variable. The economic parameters, traffic parameters, and road parameters are used to reflect the effects of different hierarchical structures so as to complete the determination of the road network hierarchical structure and optimize the plan [20].

After node importance calculation and adjustment, the nodes are sorted according to the importance of the nodes, the functional status of different nodes in the planning area is determined, and the nodes are divided into different levels to determine the main control points of the route layout of different levels.

Identification of adjacent nodes between different levels is as follows:

$$a = \frac{\sum_{i-1}^{N} X}{N}. \tag{12}$$

Step 1. Merge the nodes of the adjacent level into this level and recalculate the mean value of the importance of the M nodes in the level after merging

$$b = \frac{\sum_{i-1}^{M} X}{M}. \tag{13}$$

Step 2. Construct a statistic:

$$t = \frac{a - b}{S(a - b)}. \tag{14}$$

Table 1: The layout of the road network and nodes when the connectivity takes different values.

Connectivity value	1.0	2.0	3.15	3.21
Node connectivity	Two-way connection	Four-way connection	Six-way connection	Six-way connection
Road network layout	Tree structure	Lattice structure	Lattice plus diagonal structure	Equilateral triangle structure

Table 2: Different connectivity values of different planned target road networks.

Road network connectivity	Low	General	High	Higher
Connectivity value	$C < 1.0$	$1.0 < C < 2.\ 0$	$2.\ 0 < C < 3.\ 14$	$C > 3.14$

This quantity obeys the t distribution with $N + M$-2 degrees of freedom, where $S(a - b)$ is

$$S(a-b) = \sqrt{\frac{(N-1)S_1^2 + (M-1)S_2^2}{N+M-2}} \cdot \sqrt{\frac{1}{N} + \frac{1}{M}}. \tag{15}$$

In the above formula, S_1, S_2 are the standard deviations of the importance of each node before and after the level merging.

Expressed by the weighted average of the technical grades of the various road sections in the area, the level of the road will directly affect the traffic operation of the road, as shown in Figure 5.

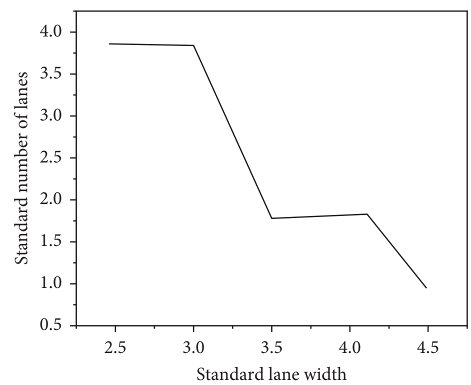

Figure 5: The number of standard lanes and lane widths for each class of highway.

4. Results and Analysis

The evaluation index system of rural road network planning is composed of several indexes. The meaning of each index is different, due to the same degree of influence on the evaluation results, and the importance of the evaluation object is different. Therefore, after the evaluation index is determined, the relative importance of each index is expressed by assigning different weight values to them [21]. The determination of index weights uses the analytic hierarchy process, which integrates the qualitative and quantitative mixed problems into a unified whole for analysis and divides the entire system into a target layer, a criterion layer, and a decision-making layer. By establishing a comparison matrix to compare each element layer by layer, the weights of indicators at the criterion level and the evaluation values of each plan at the decision-making level are obtained. The calculation steps are as follows:

4.1. Building a Hierarchical Structure. The evaluation index system of rural road network planning based on the above mentioned is the hierarchical structure of evaluation, as shown in Figure 6.

4.2. Constructing a Judgment Matrix. The judgment matrix represents the relative importance between two elements. The judgment matrix $B = (b_{ij})$ is determined, where b_{ij} is the importance of B_I relative to B_I, as shown in Table 3.

The value of b_{ij} is determined by comparing the relative importance of each element. The value of b_{ij} is shown in Table 4.

If the weight value of each index is directly derived from the eigenvector corresponding to the maximum eigenvalue of the judgment matrix, the maximum eigenvalue of the established judgment matrix is required to be completely consistent. The steps of the consistency check method are shown in Figure 7.

Statistical analysis of social and economic indicators over the years, the use of the quadratic exponential smoothing method to predict the forecasting model, and indicator values of various indicators in the planning year are shown in Table 5:

The forecast of traffic demand mainly uses the relationship between traffic demand indicators and socioeconomic indicators, and the elastic coefficient method is used for forecasting. The traffic indicators over the years are shown in Figure 8, and the predicted models and predicted results are shown in Table 6 [22].

Comprehensive evaluation utilizes two methods: value analysis method and fuzzy comprehensive evaluation. Since only one planning plan was made for the planning area in this case, there is no selection and comparison of multiple plans. The value analysis method is directly used for comprehensive evaluation. The index values of the evaluation indexes of the scheme are processed into dimensionless processing. The dimensionless evaluation indexes are obtained after processing each evaluation index, as shown in Table 7.

Combining the weight of each index, the comprehensive evaluation index value is 0.8. It can be seen that the rural

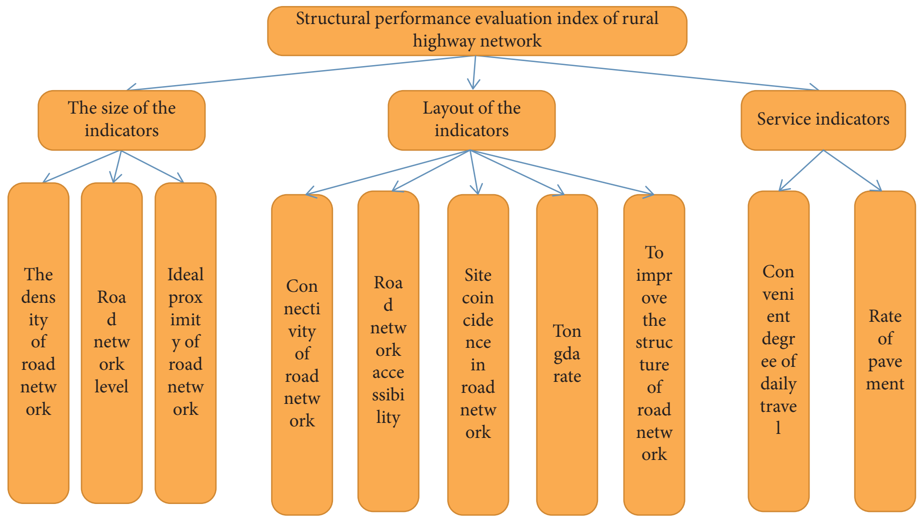

FIGURE 6: Evaluation index system diagram of rural network planning layout.

TABLE 3: NXN order judgment matrix.

A	B1	B2	...	BM
B1	B11	B12	...	B1M
B2	B21	B22	...	B2M
...	...	...	...	...
BM	BM1	BM2	...	BMM

TABLE 4: Comparison and judgment value of each element.

Scaling	Definition	Instruction
1	Equally important	By contrast, they are equally important
3	The important ones are obvious	In contrast, one of these two elements is more important than the other
5	It is very important	Of these two elements, one is clearly more important than the other
7	Extremely important	In contrast, one of these two elements is much more important than the other
9	It is very important	Comparing two elements, one is definitely more important than the other
2 4 6 8	The compromise between the above two adjacent judgments	Quantitative scale when the above two adjacent standards are compromised
The reciprocal of the above numbers	Inverse comparison	The reciprocal indicates how unimportant the two elements are when compared

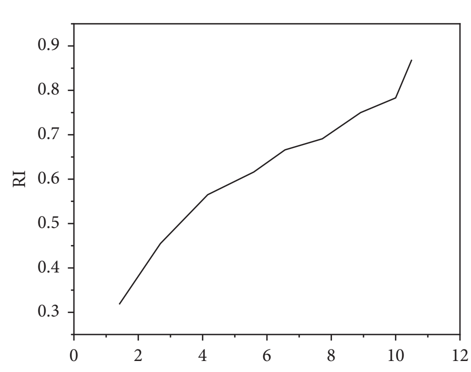

FIGURE 7: RI value selection.

Table 5: Socioeconomic index prediction models and index values.

Index	Predictive model	Predictor value
Population (10,000 people)	$Y = 24.01 - 0.07X$	23.65
Gross domestic product (ten thousand yuan)	$Y = 24.01 - 0.07X$	130370

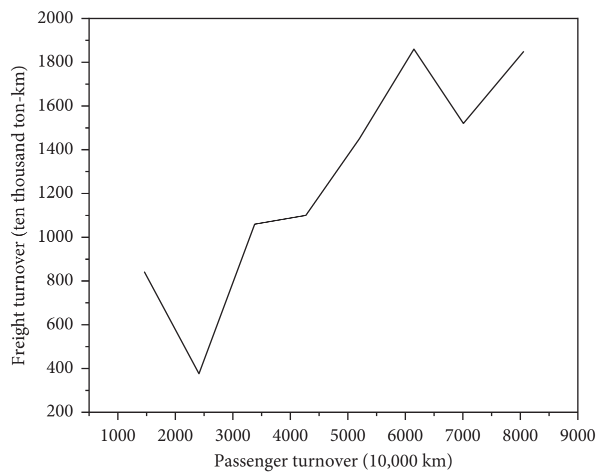

Figure 8: Highway passenger and freight turnover in Yuanba district over the years.

Table 6: Forecast models and index values of highway passenger turnover and freight turnover over the years.

Index	Predictive model	Correlation coefficient	Predictor value
Passenger turnover (10,000 people/km)	$\mathrm{Ln}\ (Y) = 2.8231\mathrm{Ln}(X) - 23.413$	0.9050	10578
Freight turnover (10,000 tons/km)	$\mathrm{Ln}\ (Y) = 0.8169\mathrm{Ln}(X) - 1.4328$	0.9414	3290

Table 7: Evaluation of nondimensional index value table.

	Primary indicator name	Secondary indicator name	Dimensionless index evaluation value of secondary index
Evaluation system	Scale index	Road network density	0.64
		Road network grade level	0.81
		Road network scale	0.77
	Layout index	Ideal proximity	0.73
		Connectivity	1
		Township rate	0.8
	Service index	Completeness	1
		Pavement rate	0.6

road network planning scheme is more reasonable and can adapt to the development of social economy.

5. Conclusion

Transportation is the prerequisite for the development of rural society. As one of the infrastructures of rural society, the planning and development of rural roads are paid more attention to. The transport efficiency of road traffic is directly affected by the development of the rural road network and also directly affects the pace of rural social and economic development. This paper analyzes the characteristics of rural roads and road planning through a series of in-depth studies on the layout of rural road network planning in China, by using remote sensing technology and computer technology. Combining with the social and economic status of my country's rural areas, the researched theory is applied to rural road planning, and the correctness of the theory in practical applications is verified. Combining the calculation of the weight of each index, the comprehensive evaluation index value is 0.8, and the planning scheme is comprehensively evaluated. The evaluation results show that the program better supports the local social and economic development.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest with any financial organizations regarding the material reported in this manuscript.

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