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A hybrid model for scale forecast of regional highway network[1]

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Abstract. A hybrid method for improvement of accuracy and reliability of scale-forecast and obtaining the optimal hierarchical structure of highway network in Hangzhou is proposed. Firstly, drawbacks of traditional scale-forecast methods of highway network are illustrated. Then, a novel prediction method which is based on BPNN and Markov chain is proposed. After that, a multi-objective programming (MOP) model is established to obtain the optimum technical grade structure of highway network. Finally, the scale of highways and their optimal hierarchical structure in the year of 2015, 2020 and 2025 is obtained.

Key words. Highway transportation, highway network, scale forecast, BP neural network, Markov chain, multi-objective programming.

1. Introduction

The forecast of regional highway network is an important part of regional transportation planning. The study by Chen et al. [1] revealed that scale forecast was of great importance in the planning of regional highway network. Qi and Chen [2] indicated that development of highway network should fit into location characteristics of regional transportation and functional requirements for highway traffic. Marin [3] showed that rational scale of a highway system referred to efficient configuration of the transportation system in which supply and demand reach the equilibrium state.

Rational highway network scale should meet the demands of regional economic and social activities by relatively small total mileage, and make the configuration

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of highway in all grades optimized, which was conducted by Nogués and González-González [4] and Wang and Han [5].

Li and Chen [6] listed methods mainly incorporate territory coefficient method, connectivity method, analogy method, and time series method, etc. Jha et al. [7] pointed out that such methods go against the evolvement rule of highway network, and the thought was proved wrong by Tsou et al. [8]. Traditional prediction methods attach little importance to the grade structure and give little consideration to influences of grade structure of highway on supply capacity, as concluded by Aldrich et al. [9] and Bonnafous et al. [10]. Li and Chen [6] concluded that the relevance of influence factors, subjectivity in the weight-determination and other issues would affect the evaluation accuracy of the traditional methods.

Our work in this paper is to build a model which can be applied to both the prediction and the analysis of regional highway network's rational scale. In the meantime, the model to optimize the technical grade structure of highway network are used.

2. Hybrid forecast method

2.1. Highway network scale forecast model based on BP neural network and Markov chain

2.1.1. Construction of forecast model based on BP neural network. In order to improve the convergence rate and reduce convergence error, sample data is normalized before training so that values of this data lie in the interval [0,1] which was put forward by Xu et al. [11] and Du et al. [12].

2.1.2. Result correction. According to the fitting error margin of BP Neural Network (the percentage that absolute error takes in actual value), Markov's status area can be classified by 5 states:

1. Extremely overvalued state (α^+).
2. Overvalued state (α).
3. Normal state (β).
4. Undervalued state (γ).
5. Extremely undervalued state (γ^+).

If the system's initial state vector is S_0 and the state vector is S_k after k steps of transfer, then $S_k = S_{k-1}p = \cdots = S_0p^k$, which is based on C-K Equation listed in Iwankiewicz [13] and Khmel et al. [14].

The state vector of predicted highway network scale can be achieved by One-step State Transfer Probability Matrix in the first place, which was conducted by D'Amico et al. [15] and Mukherjee et al. [16].

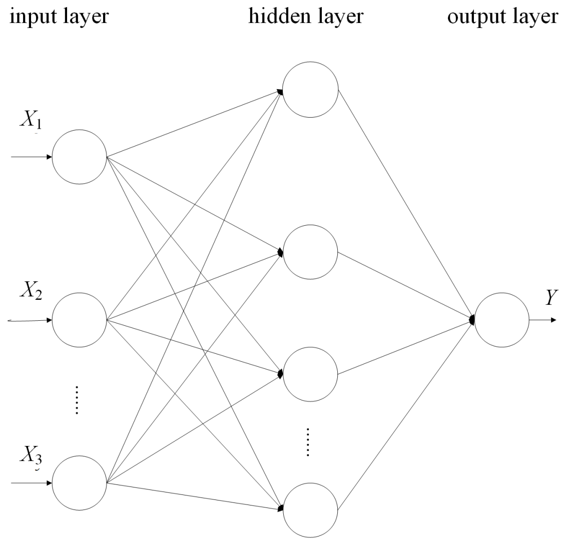

Fig. 1. BP neural network model

2.2. Multi-objective prediction method

According to the work done by Yang et al. [17] and Ojalehto et al. [18], the multi-objective programming method could take requirements put forward by highway planners and the users into consideration at the same time, and also reflect the multiple factors affecting highway network grade structure optimization. The mathematical description of highway network's technical grade structure optimization model is as follows:

2.2.1. Objective function.

- The minimum of highway network construction funds given by the formula

$$\min\left\{\sum_{j=0}^{2} p_j(t)\left[l_j(t)-l_j(t-1)\right]+\sum_{j=3}^{5} q_j(t)\left[l_j(t-1)-l_j(t)\right]\right\}, \tag{1}$$

  where l_j is the mileage of jth class highways, $p_j(t)$ is the construction cost of unit mileage for jth class highways which are newly built in year t and $q_j(t)$ is the construction cost of unit mileage for jth class highways which is rebuilt into second-class highways.

- Making the highest utilization rate of highway network highest, that can be expressed as

$$\min\left|S_N(t)-1\right|, \tag{2}$$

where $S_N(t)$ is the traffic saturation degree in tth year.

- The maximum traffic capacity of highway network, that is,

$$\max C_N(t) = \sum_{j=0}^{5} C_j(t) P_j(t)\,, \tag{3}$$

where $C_j(t)$ is the traffic capacity (capacity per day) of jth class highway in highway network in tth year. Symbol $P_j(t)$ denotes the mileage weight of its jth class highway that is given by the relation

$$P_j(t) = l_j(t)/L(t)\,,\ L(t) = \sum_{j=0}^{5} l_j\,. \tag{4}$$

- The highest average technical level of highway network expressed as

$$\min J_N(t) = \sum_{j=0}^{5} J_i(t) P_j(t)\,, \tag{5}$$

where $J_i(t)$ represents the technical level of jth section in tth year.

- And finally, the minimum average vehicle travel time of highway network expressed as

$$\sum_{j=0}^{5} K_j l_j(t) \leq Q_{\mathrm{NTF}} T_N\,. \tag{6}$$

Here, K_j is the designed traffic density of jth class highway (capacity per day); Q_{NTF} denotes the average daily amount of vehicles and their daily average kilometers in planning year(s) within the highway network. Its value can be determined from the formula

$$Q_{\mathrm{NTF}} = \left(\frac{W_1}{n_1 a_1} + \frac{W_2}{n_2 a_2} \right) \times \frac{\beta}{365}\,. \tag{7}$$

Symbols W_1 and W_2 refer to freight and passenger turnover within a region respectively, while n_1 and n_2 is the average rated tonnage and the average number of seats of both trucks and buses separately; a_1 and a_2 are the actual load rates of trucks and buses; β is the integrated correction coefficient which is related to through traffic, and T_N is the average travel time in unit mileage within a highway network.

2.2.2. Constraint conditions

- Sum of mileage

$$\sum_{j=0}^{5} l_j = L(t)\,. \tag{8}$$

- Mileage $L_{\mathrm{eq}}(t)$ of highways with different technical levels

$$L_{\mathrm{eq}}(t) = \sum_{j=0}^{5} l_j(t)\mu_j\,, \tag{9}$$

where μ_j is the conversion factor given as $\mu_j = C_j/C_2$. Symbols C_j and C_2 are the traffic capacity of jth class and secondary highways, respectively.

- Key projects

$$\alpha_j(t) \le l_j(t) \le \beta_j(t),\ j = 0, 1, 2, 3, 4, 5\,. \tag{10}$$

Here, $\alpha_j(t)$ and $\beta_j(t)$ represent the lower and upper bounds used as standards for jth class highway construction.

3. Experimental tests and analysis

3.1. Scale forecast of highway network based on BP neural network

GDP, total population, the number of civil motor vehicle ownership, passenger capacity and volume of freight traffic are regarded as nodes in the input layer of Back-Propagation Neural Network (BPNN); the total mileage of highway network is chosen as the output node. The 13th Five-Year Development Plan of Highway Transportation in Hangzhou began in 2015, ends in 2020, and looks forward to 2025. The simulation and the predicted values of BPNN are showed in Table 1 and the plot of training regression is presented Fig. 2. More information about TCM can be obtained in the research done by Yi et al. [19]. The mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean square error (RMSE) are used to compare the prediction performance between these three methods. The comparing results which shows the advantage of BPNN in dealing with nonlinear problems are shown in Table 2.

3.2. Result correction

Markov state transfer situation and Markov state transfer probability matrix P are showed in Table 3 and holistic prediction result are listed in Table 4.

3.3. Technical grade structure optimization for highway network

Data such as the average cost invested in highways of all grades, adaptable traffic and designed traffic density, etc., are derived from various surveys, statistics and related norms. All of the norms come from the newly published Technical Standard of Highway Engineering of People's Republic of China, which was compiled by Wu et al. [20]. The objective functions of the model and also constraint conditions are listed below. The input parameters are listed in Tables 5–8.

Table 1. Actual length (km) of highway network and predicted length (km) with BPNN

year	actual value (Av)	predicted value (Pv)	absolute error	relative error (%)
1994	5227	5216	11	0.21
1995	5360	5488	-128	-2.30
1996	5376	5500	-124	-2.20
1997	5570	5548	22	0.39
1998	5756	5712	44	0.77
1999	6407	6320	87	1.37
2000	6339	6422	-83	-1.29
2001	6396	6498	-102	-1.56
2002	6560	6712	-152	-2.26
2003	6793	6916	-123	-1.78
2004	7758	7590	168	2.21
2005	10644	10875	-231	-2.12
2006	12181	12108	73	0.60
2007	13463	13329	134	1.00
2008	13700	13497	203	1.50
2009	14265	13922	343	2.46
2010	14399	14143	256	1.81
2011	14586	14688	-102	-0.69
2012	14938	15074	-136	-0.90
2013	15900	15741	159	1.01
2014	16024	16197	-173	-1.07
2015		***16244***		
2016		16340		
2017		16424		
2018		16536		
2019		16647		
2020		***16713***		
2021		16815		
2022		16903		
2023		16997		
2024		17082		
2025		17169		

Table 2. Comparison between BPNN, 2-dimensional autoregressive model (AR(2)) and travel cost prediction method (TCM)

	BPNN	AR (2)	TCM
MAE	135.9	775.4	385.2
MAPE ($\times 100\%$)	1.4	7.3	3.8
RMSE	156.0	1192.5	428.7

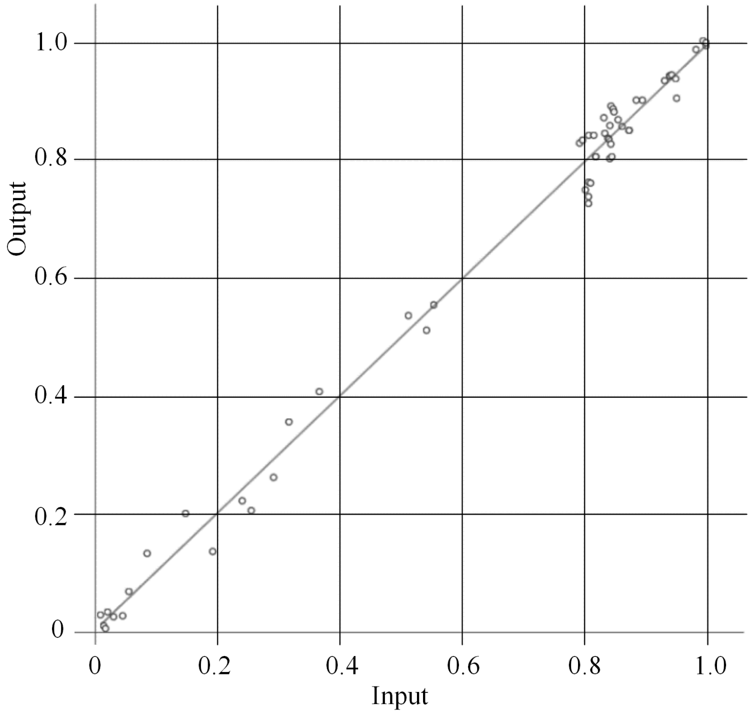

Fig. 2. Training regression of BP neural network model

Table 3. Status transfer of Markov chain

state	α	β	γ	total
α	4	1	1	6
β	1	2	3	6
γ	3	2	3	8
total	8	5	7	20

3.3.1. Objective function.

1. The minimum of highway network construction funds:

$$\min f_1 = 5000(l_0 - l_0^0) + 1200(l_1 - l_1^0) + 300(l_2 - l_2^0) + 120(l_3 - l_3^0) +$$
$$+ 70(l_4 - l_4^0) + 30(l_5 - l_5^0) = 5000l_0 + 1200l_1 + 300l_2 + 120l_3 + 70l_4 + 30l_5 -$$
$$- (5000l_0^0 + 1200l_1^0 + 300l_2^0 + 120l_3^0 + 70l_4^0 + 30l_5^0)\,, \tag{11}$$

where l_j^0 denotes the mileage of jth class highways in the last year.

2. The maximum traffic capacity of highway network:

$$\max f_2 = 55000\frac{l_0}{16406} + 30000\frac{l_1}{16406} + 15000\frac{l_2}{16406} + 6000\frac{l_3}{16406} + $$

$$+ 2500\frac{l_4}{16406} + 400\frac{l_5}{16406} = 3.352 l_0 + 1.828 l_1 + 0.914 l_2 + 0.366 l_3 + $$

$$+ 0.152 l_4 + 0.024 l_5 \,. \tag{12}$$

3. The minimum average vehicle travel time of highway network:

$$\min f_3 = 45 l_0 + 30 l_1 + 20 l_2 + 10 l_3 + 3.5 l_4 + 1.2 l_5 \,, \tag{13}$$

4. The highest average technical level of highway network:

$$\max f_4 = \frac{l_1}{16406} + 2\frac{l_2}{16406} + 3\frac{l_3}{16406} + 4\frac{l_4}{16406} + 5\frac{l_5}{16406} \,. \tag{14}$$

Table 4. Modified forecast value of highway scale of Hangzhou

year	predicted value	state vector	state vector value	predicted value interval	probability (%)
2015	16244	α	0.17	15756.7–16081.6	17
	16244	β	0.33	16081.6–16406.4	33
	16244	γ	0.50	16406.4–16731.3	50
2020	16813	α	0.46	16308.6–16644.9	46
	16813	β	0.23	16644.9–16981.1	23
	16813	γ	0.31	16981.1–17317.4	31
2025	17169	α	0.46	16653.9–16997.3	46
	17169	β	0.23	16997.3–17340.7	23
	17169	γ	0.31	17340.7–17684.1	31

3.3.2. Constraint conditions.

1. The total mileage:

$$l_0 + l_1 + l_2 + l_3 + l_4 + l_5 = 16406 \,. \tag{15}$$

2. The mileage of expressway in the Year 2015 is more than 583 km:

$$l_0 \geq 583 \,. \tag{16}$$

3. The mileage of secondary and above class highways:

$$l_0 + l_1 + l_2 \geq 2790, . \tag{17}$$

4. The mileage of fourth and above class highways

$$l_0 + l_1 + l_2 + l_3 + l_4 \geq 13125 . \tag{18}$$

Table 5. Upper bound of traffic volume for the different grade highways

Grade	Upper traffic volume (converted to standard passenger car, vehicle/day)
Highway	55000
First-grade	30000
Second-grade	15000
Third-grade	6000
Fourth-grade	2500
Substandard	400

Table 6. Planned traffic density for different grade highways in Hangzhou

Grade	Density (converted to standard passenger car, vehicle/kilometer)
Highway	45.0
First-grade	30.0
Second-grade	20.0
Third-grade	10.0
Fourth-grade	3.5
Substandard	1.2

Table 7. Turnover volume of freight and passenger for regional development planning of Hangzhou

year	W_1	W_2
2015	315.6	160.2
2020	545.8	320.8
2025	860.2	684.7

Table 8. Other related parameter values

year	n_1	a_1	n_2	a_2	β	Q_{NTF}	T_N (h/km)
2015	4.8	0.56	40	0.35	2.4	847256360	0.0172
2020	5	0.6	40	0.35	2.4	1346943249	0.0164
2025	5.2	0.64	40	0.35	2.4	2021133373	0.0156

3.3.3. Multi-objective programming model. The multi-objective programming model consists of the following relations:

$$\min R_1 d_1^+ + R_2 d_2^- + R_3 d_3^+ + R_4 d_4^- \,,$$

$$\begin{gathered} 5000 l_0 + 1200 l_1 + 300 l_2 + 120 l_3 + 70 l_4 + 30 l_5 + d_1^- - d_1^+ = e_1 \,, \\ 3.352 l_0 + 1.828 l_1 + 0.914 l_2 + 0.366 l_3 + 0.152 l_4 + 0.024 l_5 + d_2^- - d_2^+ = e_2 \,, \\ 45 l_0 + 30 l_1 + 20 l_2 + 10 l_3 + 3.5 l_4 + 1.2 l_5 + d_3^- - d_3^+ = e_3 \,, \\ \frac{l_1}{16406} + \frac{2l_2}{16406} + \frac{3l_3}{16406} + \frac{4l_4}{16406} + \frac{5l_5}{16406} + d_4^- - d_4^+ = e_4 \,, \\ l_0 + l_1 + l_2 + l_3 + l_4 + l_5 = 16406 \,, \\ l_0 \geq 583 \,, \\ l_0 + l_1 + l_2 \geq 2790 \,, \\ l_0 + l_1 + l_2 + l_3 + l_4 \geq 13125 \,. \end{gathered} \tag{19}$$

Here, e_1 denotes the funds invested in the Hangzhou's transportation planning, e_2 is the desired traffic capacity of highway network within the planning period e_3 is calculated as $Q_{\mathrm{NTF}} \cdot T_k$, and e_4 stands for the lower bound of the average technical grade of highways. The corresponding parameters and optimized values are summarized in Tables 9 and 10, respectively.

Table 9. Parameter values

year	e_1	e_2	e_3	e_4
2015	10000000	24000	14572809.39	3.10
2020	15000000	30000	22089869.28	3.06
2025	12000000	32000	31529680.63	3.02

Table 10. Highway grade optimization

Year	Highway	First grade	Second grade	Third grade	Fourth grade	Substandard	Total
2015	590	808	1550	1120	11544	794	16406
2020	650	830	1610	1260	12294	0	16644
2025	705	885	1700	1457	12250	0	16997

4. Results and discussion

It can clearly be seen from the outcome that the growth rates of highway-scale with different grades, except for the fourth grade and substandard highway, are steady. This growth trend is reasonable by comparatively analyzing the city's economic and social development status and planning under the condition of "new normal". And the growth rate of the total scale between 2020 and 2025 is faster than that between 2015 and 2020 due to the fact that Hangzhou was the host city of G20 summit in 2016 and the Asian Games in 2022 may account for it. Heggie [21] showed the impacts which was brought by Olympic Games on highway construction. In other words, the objective functions and the constraints set in the paper is rational.

The substandard highway is diminished to 0, it is in accordance with the initial 13th Five-Year Plan of Hangzhou. It reflects that the content of key projects in the constraints is acceptable. In the year of 2020, the scale of fourth grade will rise to 12294, while this figure will decrease to 12250 five years later. All substandard highways convert to the fourth grade highway in 2020, and it may explain the reason why the scale of the fourth grade highway has an increase. In this 10-year period of time, the scale of the fourth grade highway represents a declining trend. It conforms to the expectation of the optimal structure of regional highway network. So the model built in this paper can be applied to both the prediction and analysis of regional highway network's rational scale.

5. Conclusion

This article adopts the method of hybrid forecast and comprehensively utilizes Back-Propagation Neural Network, Markov chain and multi-objective programming method to improve the accuracy and the reliability of forecasting. Highway network mileage and its grade structure are both predicted, which can better reflect the quantity and quality requirements of the development of the regional highway network. As a result, regional highway network planning method is optimized.

In view of the complexity of highway network, more improvements should be made when deciding the nodes in the input layer of BPNN as well as the classification of Markov's status area. Meanwhile, some related factors, such as land use and natural resources, are not considered in the presented model. Further researches may focus on taking these factors into consideration when set objective functions and constraints. In addition, different prediction approaches (statistical methods (Zou et al. [22], Zou et al. [23]) and other machine learning methods (Jiang et al. [24]) will be considered to evaluate the performance of the proposed model.

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