Postprint: Short-Term Vacant Parking Space Prediction Method for Large Parking Lots

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Abstract

To enhance the performance of intelligent transportation systems and parking lot utilization, this study investigates short-term prediction of vacant parking spaces in large parking lots. A hybrid forecasting method based on grey theory, BP neural network, and Markov chain is proposed to improve prediction accuracy and timeliness. The method first employs grey theory to process data and weaken its randomness, then trains an artificial neural network to obtain quantitative prediction results, and finally utilizes a Markov chain to eliminate systematic random errors to derive the final result. Experimental results demonstrate that this hybrid forecasting method effectively improves prediction accuracy, with predictions conforming to the variation patterns of actual parking lot data. This provides a reliable basis for drivers to make reasonable parking lot selections in advance and can effectively improve parking space utilization rates.

Full Text

Preamble

Title: Short-Term Prediction Method for Free Parking Spaces in Large Parking Lots

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Abstract: To improve intelligent transportation system performance and parking lot utilization, this paper addresses short-term prediction of free parking spaces in large parking lots by proposing a combined forecasting method based on grey theory, BP neural networks, and Markov chains. The method first uses grey theory to process data and weaken its randomness, then trains an artificial neural network to obtain quantity predictions, and finally employs a Markov chain to eliminate random errors from the system to produce final results. Experiments demonstrate that this combined forecasting method effectively improves prediction accuracy, with results conforming to actual parking lot data variation patterns. This provides drivers with a reliable basis for making reasonable parking choices in advance and can effectively improve parking space utilization.

Keywords: free parking space; grey neural network; prediction; Markov chain

0 Introduction

With economic development and accelerated urbanization, vehicle ownership continues to grow rapidly, while static traffic facilities such as parking lots lag behind in construction, gradually expanding the shortage of parking spaces and making parking problems a major challenge in urban transportation [1]. Parking guidance systems aim to improve the utilization rate of parking lots and adjacent roads by providing drivers with information about parking lot locations, available space counts, and road traffic conditions through multiple channels, guiding them to park quickly and accurately. Currently, parking guidance systems primarily use hierarchical indicator signs to display parking lot locations and available space counts to guide drivers. However, due to real-time changes in parking space information, the information dissemination radius cannot be too large; otherwise, the number of free spaces drivers see may differ significantly from the actual count upon arrival, potentially leaving them without a parking space. Therefore, beyond displaying current availability, accurate short-term predictions of free parking spaces are beneficial for enabling drivers to make reasonable choices based on their estimated arrival time.

Regarding short-term prediction of available parking spaces, literature [2,3] proposes a prediction method based on wavelet transform and particle swarm wavelet neural network combination models. This approach uses wavelet transform to analyze input data, then predicts parking spaces through wavelet neural networks, improving accuracy but consuming substantial time and reducing efficiency. Literature [4] presents a short-term free parking space prediction method based on wavelet-ELM+ neural networks, which decomposes original data into different components for prediction, improving accuracy and using ELM neural networks to enhance training speed. Literature [5] studies short-term effective parking spaces using a Markov prediction model, leveraging grey theory' s advantage with small sample sizes to establish a GM(1,1) prediction model, then correcting results with a Markov model to reduce relative error. However, grey prediction itself has weak nonlinear processing capabilities and cannot adapt well to complex prediction systems. Literature [6-8] applies neural network methods, achieving relatively ideal prediction results. Neural network models can effectively describe complex nonlinear problems, but when training sample sizes are insufficient, prediction errors are often unsatisfactory. Literature [9-11] adopts time series methods, converting all influencing factors into temporal factors, but due to imprecise conversion, produces large errors and low prediction accuracy. Literature [12] applies chaotic time series methods to predict parking lot free spaces, achieving good results in prediction speed but with room for improvement in accuracy.

Due to the high complexity, randomness, and uncertainty of urban parking behavior, short-term free parking space prediction presents significant challenges. As prediction time intervals shorten, the uncertainty of free space changes increases, making it more difficult to design high-precision mathematical models. Therefore, employing intelligent prediction techniques and fusion methods using multiple prediction models represents an effective approach and development trend for improving short-term free parking space prediction accuracy.

This paper builds upon artificial neural networks by adding a grey layer before the network to preprocess input data and a whitening layer after the network to restore grey output information. The grey processing generates new data that is more easily approximated by the neural network' s nonlinear activation functions, greatly reducing network learning time while improving prediction accuracy and convergence speed.

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1 Principle of Short-Term Parking Space Prediction Model

As parking lot scales expand and traffic networks become increasingly complex, short-term prediction of free parking spaces exhibits more pronounced characteristics of time-varying, complexity, and nonlinearity. Single prediction models can no longer meet existing system requirements.

As described above, grey prediction models and neural network models can be organically combined into a grey neural network model. This model integrates grey systems with classical BP neural networks, using the grey model' s advantages of small sample requirements and ability to weaken data randomness to compensate for the neural network' s weaknesses of large sample requirements and slow training with random samples. Conversely, the neural network' s strong nonlinear mapping capabilities and high-speed self-learning and adaptive abilities can compensate for the grey model's weak nonlinear processing and adaptive capabilities. This combination fully utilizes both models' advantages to improve prediction accuracy, making it suitable for short-term free parking space prediction. Considering that combination models may produce relatively large errors in some predictions, Markov chains can further correct results to improve accuracy.

The difficulty and focus of short-term prediction is improving accuracy and timeliness. Traditional parking space prediction methods only explore variation patterns from historical data itself and rely on large historical samples with low precision. Therefore, it is necessary to re-analyze and integrate factors affecting parking spaces before making predictions.

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2 Construction of Improved Grey Neural Network Prediction Model

2.1 Grey Neural Network Prediction Method

Let the original sequence of grey system characteristic values be denoted as $x^{(0)}(t)$ for $t = 0, 1, 2, \ldots, N-1$. The sequence generated by first-order accumulation, denoted as $x^{(1)}(t)$, exhibits exponential growth patterns and can therefore be fitted and predicted using a continuous function or differential equation. The differential equation expression for a grey neural network model with n parameters is:

$$\frac{dy_1}{dt} + ay_1 = b_1 y_2 + b_2 y_3 + \cdots + b_{n-1} y_n \tag{1}$$

where $y_1, y_2, \ldots, y_n$ are network input parameters; y_1 is the network output parameter; and $a, b_1, b_2, \ldots, b_{n-1}$ are differential equation coefficients.

The time response function of Equation (1) is:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b_1}{a} y_2(k+1) - \cdots - \frac{b_{n-1}}{a} y_n(k+1)\right) e^{-at} + \frac{b_1}{a} y_2(k+1) + \cdots + \frac{b_{n-1}}{a} y_n(k+1) \tag{2}$$

Equation (2) can be transformed into:

$$\frac{d\hat{x}^{(1)}(t)}{dt} = \frac{b_1}{a} y_2(t) + \cdots + \frac{b_{n-1}}{a} y_n(t) - \hat{x}^{(1)}(t) \tag{3}$$

Mapping the transformed Equation (3) into a BP neural network yields a grey neural network with n input parameters and 1 output parameter. The grey BP network topology is shown in [Figure 1: see original paper] [14].

In Figure 1, LA is the input parameter layer; LB is the hidden layer; LC is the output layer; LD is the output layer; ω_{ij} are network weights; and $y_1, y_2, \ldots, y_n$ are network input parameters.

2.2 Improved Grey Neural Network

Although grey neural networks can achieve good prediction results in practice, some predicted values have excessively large relative errors compared to actual values, leading to unstable prediction results. Therefore, error residuals need correction. The flowchart of the Markov chain improved grey neural network prediction model is shown in [Figure 2: see original paper].

The difficulty in controlling grey model prediction accuracy within a certain range stems from the volatility and disorder of original sample data. However, neural networks require large sample sizes to achieve ideal results, hence the introduction of grey systems to build grey neural network models that reduce dependence on sample size [13].

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3 Case Study and Analysis

3.1 Mechanism Analysis of Free Parking Space Variation

Based on the periodicity and similarity of traffic flow transformation trends, we hypothesize that temporal variation patterns of free parking spaces should exhibit similar characteristics. Taking an underground parking lot of a commercial center in Lanzhou as an example, we analyzed temporal variation data of free parking spaces on both weekdays and holidays. The investigation revealed strong similarity in free parking space variation trends at the same time on the same day across different weeks, and similar patterns exist for Monday through Friday. Therefore, free parking space variation patterns are periodic and similar.

Plotting the sampled free parking space count data as a curve yields the variation trend shown in [Figure 3: see original paper].

3.2 Case Validation Analysis

Based on the above analysis, this experiment used actual interface data from the management system of an underground parking lot at a commercial center in Lanzhou, collected in October at 10-minute intervals, totaling 7,284 parking space records. The input parameters for the combined network included data at time t, $t-10$ min, $t-20$ min, $t-30$ min, and $t-40$ min (after normalization) plus three influencing factors. Taking 16:30~17:00 daily from October 5~12, 2016 as an example, the data is shown in . Using this sample composition method and excluding nighttime data, 1,601 samples were obtained. Of these, 1,200 samples were used as training data for the grey neural network, and 208 samples as test data.

The normalization formula for original data is:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

where x_i is the original data, x_i' is the normalized data, $x_{\min}$ is the minimum parking space count, and $x_{\max}$ is the maximum parking space count. Denormalization is performed afterward.

After comprehensive consideration of other factors affecting parking spaces, surrounding traffic flow, weather conditions, and event occurrence were incorporated as input parameters to enhance network generalization capability. The grey neural network model for free parking spaces should have 3-dimensional inputs and 1-dimensional output predictions. Combining with Figure 1, the grey network model structure for parking space quantity prediction is 1-1-4-1: the LA layer has one input neuron node receiving time series t; the LB layer has 1 neuron node; the LC layer has 4 neuron nodes (the first neuron expands the BP neural network, with subsequent inputs being parking lot surrounding traffic conditions, weather conditions, and event occurrence); the LD layer has 1 neuron outputting the predicted free parking space count. MATLAB software was used to implement the grey neural network prediction model training program.

Timeliness is a practical value manifestation of short-term prediction systems. Therefore, sample selection must fully consider timeliness: the sampling period should not be too large, but shorter intervals increase random interference effects and make free parking space variation more volatile. Through comparative analysis, a 10-minute interval for prediction is reasonable. Sample data timeliness also manifests in that current predictions are strongly correlated not only with historical data but also with real-time free parking space counts from the previous moment, which must also be included as an input.

However, converting the free parking space prediction problem solely into a time series problem yields unsatisfactory results because it only considers the time dimension while ignoring other influencing factors. Investigations show that weather conditions, surrounding road traffic conditions, and large events near the parking lot all significantly impact free parking space counts. When determining prediction system input variables, besides historical data, weather, surrounding traffic, and event occurrence must be included as neural network input variables.

When sample factor variations are small and correlations between factors are stable, prediction results are more meaningful for practical guidance. This paper selects historical parking space data from the same time on the same day of different weeks and real-time parking space data from the moment preceding the prediction period as system inputs. Additionally, other factors are assigned different input parameter values based on impact magnitude to improve accuracy and timeliness. This paper selects weather conditions from the 15-minute period before prediction: poor weather (rain, snow) is represented by 0.5, good weather by 0. For surrounding road traffic flow, data from 10 minutes before prediction is used. According to real-time traffic flow standards: when vehicle count at a designated intersection is below 250 per 15 minutes (smooth flow), it is represented by 0.75; 250-400 vehicles per 15 minutes (congested) by 0.45; and above 400 vehicles per 15 minutes (jammed) by 0.15. Large events near the parking lot are represented by 1, no events by 0.

The trained network was tested using test samples to verify generalization capability. Prediction results are shown in [Figure 4: see original paper], displaying predictions every 10 minutes from 9:00 to 17:00, compared with BP neural network predictions. This verifies that grey neural networks are suitable for small-sample prediction problems, though some samples show large relative error fluctuations (shown in). Therefore, Markov chain correction is introduced.

3.3 Markov Residual Correction

The Markov chain corrected grey neural network modeling process calculates relative errors between predicted and measured values from the prediction model, divides the error range based on magnitude, and establishes state division intervals using the mean-variance method [15]. Relative errors are then classified by state, state transition probability matrices are calculated, initial state vectors are determined, and predicted time period states are obtained to further derive correction values.

Based on relative errors from , the Markov chain state intervals are divided as: mean $\bar{X} = 2.95$, standard deviation $s = 10.41$, with classification standards: E1[-30.5, -8.501], E2[-8.501, -2.2555], E3[-2.255, 8.155], E4[8.155, 14.401], E5[14.401, 30.5]. The grey neural network prediction errors are classified accordingly, with results shown in .

The one-step transition probability matrix is then determined as:

$$P = \begin{bmatrix} 0.2 & 0.8 & 0 & 0 & 0 \\ 0 & 0.4 & 0.6 & 0 & 0 \\ 0 & 0.333 & 0.167 & 0.25 & 0.25 \\ 0 & 0.125 & 0.125 & 0.56 & 0.19 \\ 0 & 0 & 0.25 & 0 & 0.75 \end{bmatrix}$$

From , grey neural networks adapt to small-sample prediction, but data volatility causes unsatisfactory relative errors in some periods (e.g., 10:30~11:00, 12:30~13:00). Markov chain can correct these residuals. Based on state classification results from , state vectors for each time period are determined to solve for predicted corrections.

The Markov chain corrected grey neural network model predictions are shown in , compared with BP neural network and grey neural network models.

Experiments were conducted on an Intel i3 Windows 7 system running MATLAB simulation software. For grey neural network Markov chain combination prediction, maximum iterations were set to 1,000, with network training time of approximately 2 minutes, improving result effectiveness. The final corrections show that the Markov chain corrected grey neural network model improves prediction accuracy, making corrected values closer to measured values.

4 Conclusion

To address short-term free parking space prediction, this paper employs a combined grey neural network prediction model corrected by Markov chains. Simulation results demonstrate that the combined model can accurately predict short-term free parking space counts for an underground parking lot in Lanzhou Wanda Plaza, improving both prediction accuracy and training speed. The maximum relative error between corrected predictions and measured values decreased from 28.81% to 13.51%, showing that the optimized neural network achieves higher precision.

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Note: Figure translations are in progress. See original paper for figures.