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Available parking space occupancy change characteristics and short-term forecasting model

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Abstract: Based on an available parking space occupancy (APSO) survey conducted in Nanjing, China, an APSO forecasting model is proposed. The APSO survey results indicate that the time series of APSO with different time-sections are periodical and self-similar, and the fluctuation of the APSO increases with the decrease in time-sections. Taking the short-time change behavior into account, an APSO forecasting model combined wavelet analysis and a weighted Markov chain is presented. In this model, an original APSO time series is first decomposed by wavelet analysis, and the results include low frequency signals representing the basic trends of APSO and several high frequency signals representing disturbances of the APSO. Then different Markov models are used to forecast the changes of low and high frequency signals, respectively. Finally, integrating the predicted results induces the final forecasted APSO. A case study verifies the applicability of the proposed model. The comparisons between measured and forecasted results show that the model is a competent model and its accuracy relies on real-time update of the APSO database.

Key words: available parking space occupancy; change characteristics; short-term forecasting; wavelet analysis; weighted Markov chain

Whether a parking lot has available parking spaces or not is an important concern when drivers choose optimal parking lots[1]. Accurate forecasting of available parking spaces of parking lots is the basic theory of the parking guidance and information system (PGIS), which can help drivers choose optimal parking spaces and prepare rational travel plans before trips.

Parking spaces included in PGIS are those spaces which allow vehicles to park in public parking lots. Fixed parking spaces hired by individuals are not included in PGIS. In this paper, a new index in terms of available parking space occupancy (APSO) is put forward to describe utilization of parking spaces in a parking lot. Available parking space is defined as parking spaces which are not occupied by vehicles or other goods and can be used to park vehicles in an open parking facility[2]. APSO is the ratio of available parking spaces to the total number of parking spaces.

The change characteristics of parking spaces in a parking lot is influenced by many factors such as the type and location of the parking lot, weather, traffic flow and accidents around the parking lot. Multi-attributes results in APSO change complexity and randomness. At present, the main forecasting method of parking space is the BP neural network[3-4]. But the BP neural network has some disadvantages such as the slow convergence speed and the difficult train of weights.

This paper aims at developing a short-term forecasting model for APSO. Considering a good application of a Markov chain and wavelet analysis in the forecasting of an unstable time series[5-6], a model combined with wavelet analysis and weighted Markov chain forecasting model is proposed to forecast the APSO. According to a parking facility's time records of vehicle arrival and departure, the change characteristics of the APSO are analyzed in this paper. Then, the wavelet analysis-weighted Markov chain forecasting model is put forward. Finally, a case study is presented for verifying the applicability of the proposed model.

1 Short-Term Change Characteristics of APSO

1.1 Account method of APSO

Many parking lots have a charging management system, and vehicle arrival and departure time from the database of the system are available[7]. It is assumed that A_i $(i=1,2,\ldots,m)$ is the number of vehicles arriving at a parking lot and L_i $(i=1,2,\ldots,m)$ is the number of vehicles leaving a parking lot in an interval i. The available parking spaces at the end of an interval

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$i(X_i)$ can be represented as $X_i = X_{i-1} - A_i + L_i$. Suppose that C represents the total parking spaces of a parking lot and the APSO (R_i) can be represented as $R_i = X_i / C$. Then the time series of the APSO $\{R_1, R_2, \ldots, R_m\}$ can be obtained.

1.2 Analysis of short-term change characteristics

1) Periodicity and similarity

Taking Bainaohui underground parking lot in Nanjing city as an example, the variation characteristics of the APSO are analyzed based on the statistical data from 2005-12-12 to 2005-12-18 (see Fig. 1). During this week, the APSO every day change tendencies are approximate. However, due to different travel purposes, the change tendencies between workdays (from Monday to Friday) and weekends (Saturday and Sunday) are different. Compared with workdays, weekend travel purposes are mainly for entertainment.

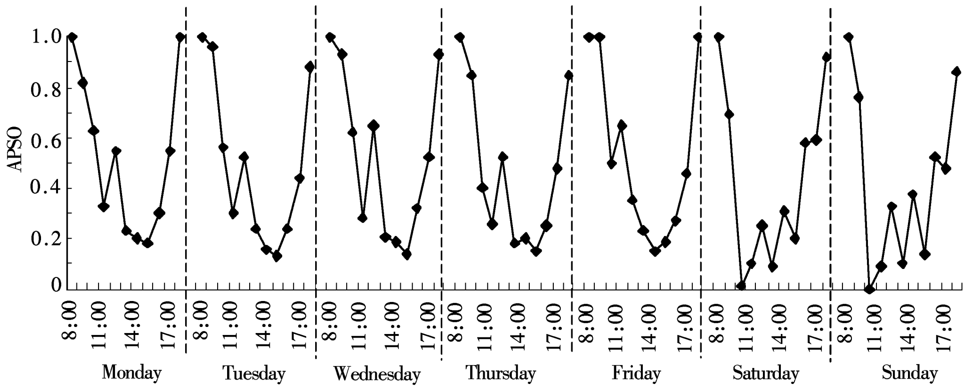

Fig. 1 Weekly change curve graph of APSO

2) Randomness

Fig. 2 shows the change characteristic of the APSO on 2005-12-12 with 5, 10, 15 and 30 min time intervals in the Bainaohui underground parking lot. The results indicate that the APSO has very strong randomness in different intervals, and the fluctuation of the APSO increases with the decrease in time-sections. Especially, the change trends from 11:00 a.m. to 5:00 p.m. are the most frequent and random periods during one day.

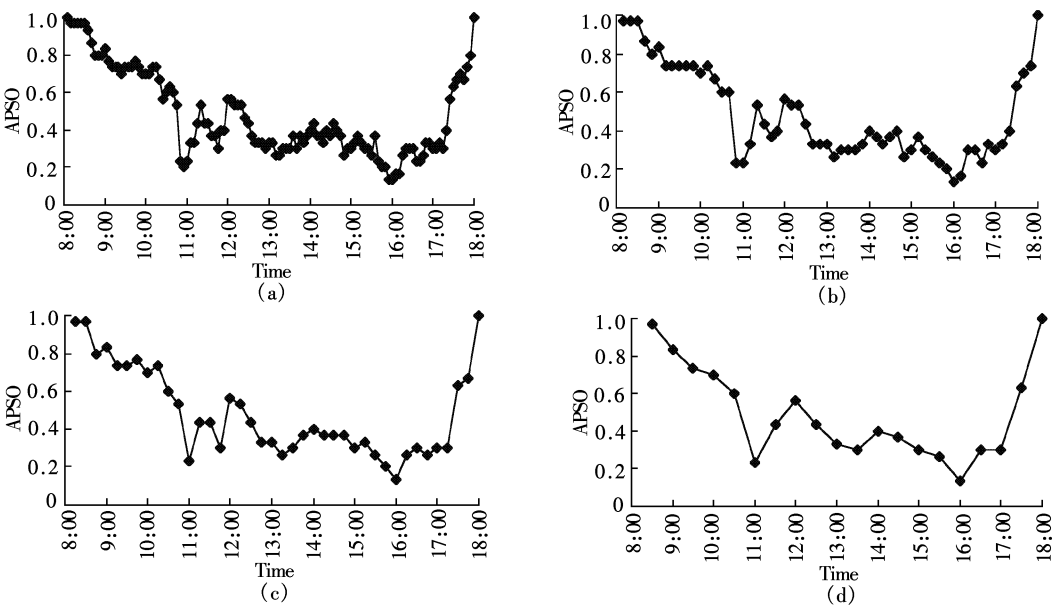

Fig. 2 Daily change curves of APSO. (a) 5 min interval; (b) 10 min interval; (c) 15 min interval; (d) 30 min interval

2 Wavelet Analysis and Weighted Markov Chain Forecasting Model

On the macro level, factors influencing the APSO can be categorized into two kinds, that is, intrinsic factors which reflect essential rules such as types, addresses and costs of parking lots and random factors which reflect random rules such as traffic around parking lots and weather. Wavelet analysis is used to separate different factors influencing the APSO in this paper. And low frequency signals reflecting basic trends and several high frequency signals expressing disturbance are separated by selecting proper wavelet functions to decompose and reconstruct original APSO time series. Low frequency signals separated by wavelet analysis are not disturbed by random factors, so common forecasting methods can satisfy their forecasting precision. The weighted Markov chain forecasting model, which is competent for forecasting uncertainties or randomly variable series, is employed to forecast the trend of high frequency signals. The Markov chain forecasting model can also be used to forecast low frequency signals. In this paper, Markov forecasting models based on these reconstructed signals are built for low frequency signals and high frequency signals, respectively. Finally, the forecasting results obtained by the above Markov models are integrated to obtain the forecasted APSO.

2.1 Forecasting procedure

First, a proper wavelet function is chosen to decompose the APSO time series. A low frequency coefficient vector $\boldsymbol{c}_N$ and high frequency coefficient vectors $\boldsymbol{d}_1, \boldsymbol{d}_2, \ldots, \boldsymbol{d}_N$ are obtained, respectively. Then low frequency signals and high frequency signals are reconstructed by an appointed wavelet function with time series C_N expressing basic trends and time series $D_1, D_2, \ldots, D_N$ expressing disturbance. Based on the $N+1$ reconstructed time series, a weighted Markov chain forecasting model results in $N+1$ results $\hat{C}_N, \hat{D}_1, \hat{D}_2, \ldots, \hat{D}_N$. Finally, adding the $N+1$ results $\hat{C}_N, \hat{D}_1, \hat{D}_2, \ldots, \hat{D}_N$ yields the forecasted APSO.

2.2 Wavelet decomposition and reconstruction

The APSO time series are discrete time series and the orthonoimal dyadic wavelet transformation which is one kind of discrete wavelet transformation is suitable for the decomposition and reconstruction of the APSO time series. So the Mallat algorithm is chosen for wavelet decomposition and reconstruction.

The Mallat algorithm[8] can be represented as

$$\begin{cases} c_{n+1} = Hc_n \\ d_{n+1} = Gc_n \end{cases} \qquad n = 0, 1, 2, \ldots, N$$

where H is the low-pass order filter; G is the high-pass order filter; N is the decomposing scale and c_0 is the original time series. Low frequency coefficient vector $\boldsymbol{c}_N$ and high frequency coefficient vectors $\boldsymbol{d}_1, \boldsymbol{d}_2, \ldots, \boldsymbol{d}_N$ can be obtained by the Mallat algorithm.

Time series decomposed by the Mallat algorithm can be reconstructed by the following function:

$$C_n = H^* C_{n+1} + G^* D_{n+1} \qquad n = N-1, N-2, \ldots, 0$$

where H^* and G^* represent the dual operators of H and G, respectively. And the reconstructed time series can be represented as $C_0 = C_N + D_1 + D_2 + \ldots + D_N$.

2.3 Weighted Markov chain forecasting

1) State division

The essentials of the Markov process and the Markov chain are the transformation of the system state. State division is the foundation of Markov chain forecasting. We usually confirm variation sections based on sample means and sample variances. When data is less, the system state should be less. And with the increase in data amount, the system state can be increased.

2) Calculation of transition probability matrix

Suppose that a time series is divided into n states (i.e., $E = \{E_0, E_1, \ldots, E_n\}$). According to historical data, the transition probability of the Markov chain can be estimated first. f_{ij} is the frequency of transition from state E_i to state E_j, where $E_i, E_j \in E$. And matrix $\boldsymbol{F} = \{f_{ij}\}_{E_i, E_j \in E}$ is designated as a transition frequency matrix. Transition probability p_{ij} can be represented as

$$p_{ij} = \frac{f_{ij}}{\sum_{j=1}^{n} f_{ij}}$$

3) Calculation of self-correlative coefficients

The self-correlative coefficient of rank k can be represented as r_k and it can be calculated by the following function:

$$r_k = \frac{\sum_{t=1}^{m-k} (x_t - \bar{x})(x_{t+k} - \bar{x})}{\sqrt{\sum_{t=1}^{m-k} (x_t - \bar{x})^2 \sum_{t=1}^{m-k} (x_{t+k} - \bar{x})^2}}$$

where x_t is the numerical value of time t; $\bar{x}$ is the sample mean and m is the time length. The self-correlative coefficient ω_k can be normalized by

$$\omega_k = \frac{|r_k|}{\sum_{k=1}^{l} |r_k|}$$

where ω_k is also the weight of the Markov chain in different time sections.

4) Weighted Markov chain forecasting results

Based on the transition probability matrix, the probability of state i can be forecasted as $P_i^{(k)}$, $i \in E$, $k = 1, 2, \ldots, l$. Weighting sums of different probabilities in the same state can be represented as $P_i = \sum_{k=1}^{l} \omega_k P_i^{(k)}$, $i \in E$. And the corresponding state I of the maximum of $\{P_i, i \in E\}$ is the forecasted state. Then level characteristic values of the fuzzy set theory can be used to confirm certain values.

2.4 Analysis of forecast error

In this paper, the mean relative error (MRE) is used as the index of error analysis and can be represented as

$$\varepsilon_{\mathrm{MRE}} = \frac{\sum_{i=1}^{N} \frac{|\hat{x}(i) - x(i)|}{x(i)}}{N} \times 100\%$$

where $\hat{x}(i)$ is the forecasted value; $x(i)$ is the actual value and N is the number of test data.

3 Case Study

Bainaohui underground parking lot in Nanjing city is used as an example to verify the applicability of the proposed model. 270 data from 8:00 a. m. on December 12 to 1:00 p. m. on December 16 with 10 min intervals are used as historical samples and data between 1:00 p. m. and 6:00 p. m. on December 16 are used as test samples.

The 270 historical samples are decomposed and reconstructed based on the wavelet toolbox of MATLAB 7.0. Sym4 is chosen as the wavelet function and four time series C_3, D_3, D_2, D_1 are shown in Fig. 3.

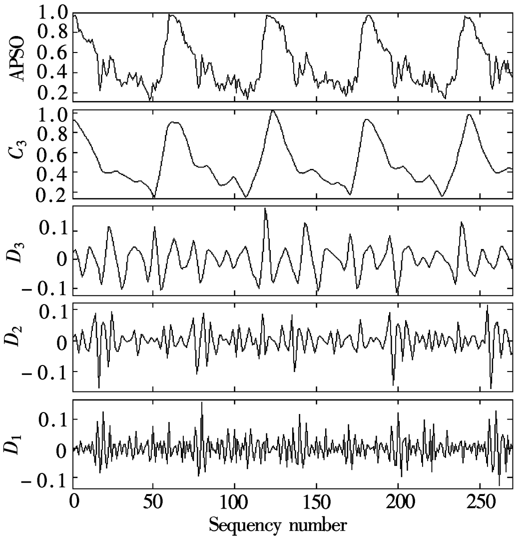

Fig. 3 Original time series and reconstructed time series

Set up the weighted Markov chain forecasting model based on four reconstructed time series C_3, D_3, D_2, D_1 and obtain the four results $\hat{C}_3, \hat{D}_3, \hat{D}_2, \hat{D}_1$. Finally, the four results can be added to yield the forecasted APSO (see Fig. 4).

The comparison between measured and forecasted results indicates that the proposed model is an efficient way to forecast a short-term APSO. The mean relative error of forecasted results is 13.9%. The results also reveal that mean relative errors from 1:00 p. m. to 4:50 p. m. increase with time elapsing, which implies that the APSO database should be updated. Mean relative errors from 5:00 p. m. to 6:00 p. m. are smaller because of the influence of random disturbance decreasing during this period.

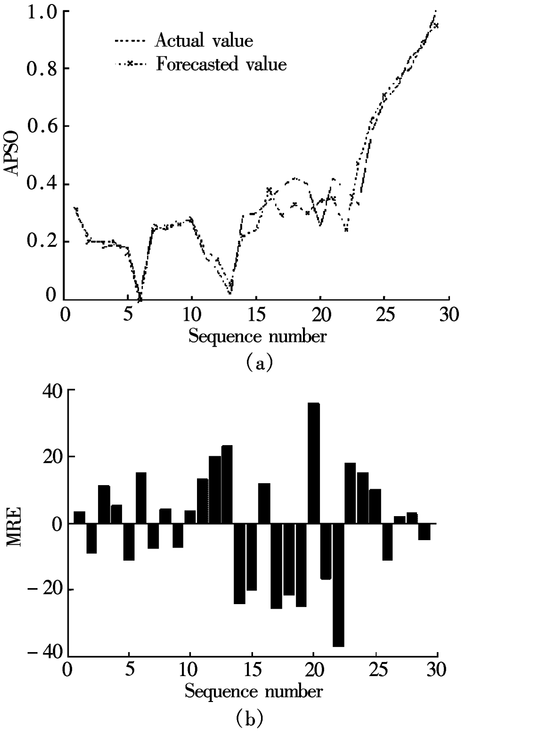

Fig. 4 Forecasted results of APSO. (a) Measured value vs. forecasted value; (b) Mean relative error

4 Conclusions

The significant contributions obtained from this study are enumerated as follows:

1) The APSO survey results indicate that the time series of APSO with different time-sections are periodical and self-similar, and the fluctuation of APSO increases with the decrease in time-sections.

2) A model combined wavelet analysis and the weighted Markov chain forecasting model is an efficient way to forecast APSO. The accuracy of this model relies on real-time update of the APSO database.

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停车场有效泊位占有率变化特性及其短时预测模型

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摘要:在某停车场泊位变化实测数据分析的基础上,建立了一个停车场有效泊位占有率短时预测模型. 南京某停车场实测泊位数据分析表明,在不同的观测尺度上,停车场有效泊位占有率具有很强的周期性和相似性,但观测尺度越小,随机性越强. 基于有效泊位占有率的这种短时变化特性,提出采用小波分析和加权马尔可夫组合模型对有效泊位占有率进行短时预测. 首先,通过选择合适的小波函数对有效泊位占有率时间序列进行多分辨率的小波分解,并对低频信号与高频干扰信号分别进行重构,然后对重构后的基本信号和不同分辨率的干扰信号分别建立加权马尔可夫预测模型,最后对各自外推的预测结果进行合成,得到最终预测结果. 实例分析表明,所提出的预测模型对有效泊位占有率的短时预测结果是有效的,但模型的预测精度依赖于有效泊位占有率数据库的实时更新.

关键词:有效泊位占有率;变化特性;短时预测;小波分析;加权马尔可夫链

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