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Short-term forecasting of available parking space using wavelet neural network model

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ABSTRACT:
The technique to forecast available parking spaces (APS) is the foundation theory of Parking Guidance Information Systems (PGIS). This paper utilizes data collected on parking availability at several off-street parking garages in Newcastle upon Tyne, England, to investigate the changing characteristics of available parking space (APS). Using this baseline data the research reported here aims to build up a short-term APS forecasting model and applies the wavelet neural network (WNN) method to the PGIS problem. After selecting optimal preferences, including training set size, delay time and embedding dimension, the APS short-term forecasting model based on WNN is built and tested using the real-world dataset. By experimental tests conducted using the same dataset, WNN's prediction performance is compared with the largest Lyapunov Exponents (LEs) method in the aspects of accuracy, efficiency and robustness. It is found that WNN prevails through a more efficient structure and employs, barely half of the computational cost compared to the largest LEs method, which could be significant if applied to real-time operation. Moreover, WNN enjoys a more accurate performance, for its prediction average Mean Square Error (MSE) is 6.4±3.1 (in a parking building with 492 parking lots) for workdays and 8.5±6.2 for weekends, compared to the MSE of largest LEs method---18.7 and 29.0, respectively.

KEY WORDS: available parking space, wavelet neural network, short-term forecasting method

1. INTRODUCTION

Along with the global trend of growth of urban populations, car ownership and usage continues to increase every year with McKinsey predicting car and light van unit ownership will increase from 1.01 billion in 2013 to 1.32 billion by 2020[1]. This growth has resulted not only in serious traffic congestion due to the over demand for road space at peak times but also acute parking shortages in many cities as demand again exceed supply, rather than constructing new parking facilities, the provision to drivers of advanced and accurate information on parking availability has been seen a more efficient and favorable solution – utilizing the parking spaces available more optimally. Parking Guidance Information Systems (PGIS) are among the most common forms of intelligent transport systems (ITS) currently in use in urban traffic management.[2, 3]. Advances in information and communication technologies have made it possible for PGIS to provide accurate updates in parking guidance information for drivers, such as: parking facilities' location; real-time availability of parking space; capacity; opening hours; parking price; predicted levels of occupancy and performance [4-6].

Drivers take multiple factors into consideration when they are searching for a parking space. The parking fee, parking availability and accessibility to their final destination, are the three attributes reported to considerably influence the driver's parking choice and decision-making process [7, 8]. Obviously, real-time available parking space (APS) is the paramount factor during the driver's parking search process [9]. Available parking space is defined as parking space which are not occupied by a vehicle or unavailable for another reason is available for a vehicle to park in[10]. Accurate forecasting of available parking spaces in parking facilities is the foundation theory of PGIS. If real-time available parking space can be predicted correctly and released timely, then drivers' parking search choice can be performed easily by selecting the most suitable parking facilities, reducing searching time, and that vehicles contribution to congestion and traffic pollution. As studied in Caicedo [11], drivers that can obtain information about parking availability are 45% more successful than those cannot get parking availability information in their parking decision-making process. In addition, managers and operators of parking facilities may foresee the performance of parking facilities and carry out timely intervention, strategic decisions to manage congestion and over-demand for parking – indeed the Tyne and Wear UTMC (Urban Traffic Management and Control) centre used by Newcastle upon Tyne and for the base data set provide prediction of parking availability on a 30 minute headway and also configures the traffic management system to cope with significant 'unusual flows' of vehicles from large events[12]. Thus, accurate forecasting of available parking space information can also help urban traffic management and control department to ease traffic congestion and control traffic demand. Therefore the forecasting of APS has attracted strong interest in recent years, which can be decomposed into a time-series modeling problem where one attempts to predict the value of a variable based on a series of past samples of the variable at regular intervals. In particular, transportation researchers have developed time series traffic prediction models using techniques such as Autoregressive Integrated Moving Average (ARIMA), nonparametric regression, neural networks, and wavelet analysis [13]. These methodologies can be classified into two main kinds: economic or statistics models and artificial intelligence models.

The economic and statistics method reveals the statistical laws of the APS time series and then predicts it according to established laws. For example, an econometric forecasting model, which uses changing conditions of the local economic as explanatory variables and other standard available data in large cities, was developed to predict two parking facilities' monthly revenues. Their work involves the predicting of occupied parking spaces over the long term, in Kansas City, Missouri. Later references began to forecast parking demand based on dynamic methodologies [14]. Arnott [15] studied parking policy from the viewpoint of economic theory, and used spatial competition among parking facilities to analyze the equilibrium of whole parking market. A study proposed by Erhardt [16] described a framework based on a market approach to modeling parking supply and cost. Considering actual parking fees paid by drivers, this model keeps the balance of parking demand and supply and forecasts appropriate parking fees' with longitudinal data.Dunning [17] developed a method to predicting parking availability based on a database with information of every parking facility. The method was tested using data obtained from a survey of remote parking facility with high demand using the simple time series method of ARIMA. Further studies conducted by Ji Y.J. [18], which combine wavelet analysis, Markov models and ARIMA, first decomposed the origin APS time series by wavelet analysis and then predicted the low frequency signals and several high frequency signals respectively. Afterwards, chaos time series techniques were applied to the APS forecasting field, which abstracts the laws of APS data by chaos analysis. SX [19]developed a weighted one-rank local-region method to predict unoccupied parking spaces based on the chaotic time series forecasting methods of historical data. Caicedo F. et al. predict real-time parking availability of parking facility with availability forecast algorithm in real-time based on a discrete choice model considering the effect of receiving availability information to characterize and predict drivers' selections [13].

Artificial intelligence is the intelligence of machines and the branch of computer science that aims to create it. Artificial intelligence models are now prevalent in the forecasting and prediction field. Yang [20] predicted available parking spaces using neural networks whose input included multiple variables such as weather, events, road traffic flow and conditions, etc. He also stated that large sample sizes need large amounts of time to execute and proposed a method to determine the number of hidden nodes. Other methods of statistics methods and artificial intelligence models, such as weighted zero-rank local-region method [21], largest Lyapunov Exponents method [22, 23] and wavelet neural networks [24-26], although not directly applied to APS forecasting domain, were introduced in short-term traffic flow forecasting, which is often similar to APS forecasting. These algorithms are discussed in the book *Dynamic prediction method of traffic flow parameters and traffic events* [27]. It suggests wavelet neural network (WNN) is a rapid and conductive method with more accuracy than back propagation neural network (BPNN) in traffic flow forecasting and demonstrated that the largest Lyapunov Exponent method prevails over local-region method in multi-step forecasting field.

However, the fact that transportation researchers more often apply time-series modeling methods to forecast short-term traffic flow rather than available parking spaces suggests that the research in this area have a wide choice of available methods to apply, but to date, lack demonstrations of practical applications to real-world statistics. Particularly, the three issues below need further study:

- **The changing characteristics of APS.** Most previous researchers, especially those simulating real time time-series data, only paid attention to workdays yet did not mention how to forecast weekend APS. This is plausible in traffic flow forecasting but unreasonable in APS, which is often particularly low on weekends in parking lots near shopping malls.
- **The preferences of WNN when reconstructing the phase space.** The methods to choose the network parameters in WNN(for example the number of hidden nodes)are well studied, but the parameters used in phase space reconstruction, such as delay time and the embedding dimension are not clearly introduced.
- **The comparative study of selected methods.** In many former studies, authors introduced one of the above methods and then evaluated its performance using different data sets. Nonetheless, the optimal methodology for different kinds of data sets may not be the same. Moreover, different forecasting environments, such as in standard workdays or holidays, may be disparate in nature and thus may benefit from different forecasting methods. For example, when simulating real-time data, wavelet neural networks (WNN) and the largest Lyapunov Exponents (LEs) method are both popular methods used nowadays. However, their performance has seldom been directly compared by experiments in previous studies.

In this paper, we analyze the changing characteristics of APS using Pearson correlation coefficients. According to the analysis, a more precise method to forecast short-term APS was proposed. A WNN model is built to forecast short-term APS and in phase space reconstruction, its parameters are determined to achieve both accuracy and efficiency. The performance comparison of WNN and the Lyapunov Exponent method in short-term APS forecasting are conducted in full-scale aspects including accuracy, soundness and the ability to deal with abnormal test set.

The remainder of this paper is organized as follows. In the next section, the changing characteristics of APS are analyzed and the strategy of choosing a training set is introduced according to the analysis. Thereafter, the algorithm of WNN is presented as a method to conduct short-term prediction of APS while its preferences are determined by scientific analysis and trials. Subsequently, the WNN based model is tested in real world data collected in Newcastle upon Tyne, England, and compared with the largest LEs method, considering accuracy, soundness and abnormal data adaptability in short-term prediction. At last, conclusions and future research are included.

2. THE CHANGINGCHARACTERISTICS OFAPS

Before introducing the predicting methodology, we first analyze the statistical property of APS, which is a crucial step where we select an appropriate forecasting model and optimal data set to train the model. Choosing the data from Jun. 2011 to Jan. 2012, collected in Eldon Multi, John Dobson Street Lot and Quayside Multi, in Newcastle upon Tyne, England, the APS data of Eldon Multi, which is a parking building attached to a shopping mall whose capacity is 492 ports, are demonstrated and analyzed in this paper, where the collection interval is 30 seconds and the analyzed time is from 06:00 to 22:00. The statistical analysis is mainly based on the study of correlation characteristics, with which the forecasting error can be reduced by measuring the degree of similarity between different days and then selecting appropriate training set[28].

2.1 Assessment Method

We introduce two parameters to describe the correlation feature of time-series data:

Pearson coefficient: This coefficient, referred to as r below, is calculated by means of the following equation:

$$-1 \le r = \frac{\sum\left(X - \overline{X}\right)\left(Y - \overline{Y}\right)}{\sqrt{\sum\left(X - \overline{X}\right)^2 \sum\left(Y - \overline{Y}\right)^2}} \le 1 \qquad (1)$$

In this APS forecasting research, X and Y are two matching APS observations for different days. The greater the r(X, Y), the more related these days' APSs will be. Thus a lower prediction error can be achieved when using one of these similar data as a part of the training set to forecast another. However, as Pearson coefficient cannot measure the absolute similarity of two days' APS, another parameter, the absolute value of the difference, is further involved.

Absolute value of the difference: The absolute value of the difference, referred to as d below, is introduced to measure difference in APS absolute values, which is defined as below:

$$\mathrm{d} = \frac{\sum|\mathrm{X}-\mathrm{Y}|}{\mathrm{n}} \qquad (2)$$

Where n is the length of X and Y.

As X and Y are time series of observations taken at 1 min temporal resolution with 2*60*18 components, n equals to 2160 here. The lager the average distance is the larger difference, which means the weaker collections, between X and Y will be. When comparing the similarity of several pairs of matching observations, their r parameters are first compared and then d parameters are compared to further evaluate the correlation feature if their r values are approximately equal.

2.2 Assessment

Choosing data from the Newcastle UTMC from 4-9-2011 to 17-9-2011, the sample time interval is 1minute.The interval from 6:00 to 22:00 every weekday is analyzed and the weekly APS curve is shown in figure 1.

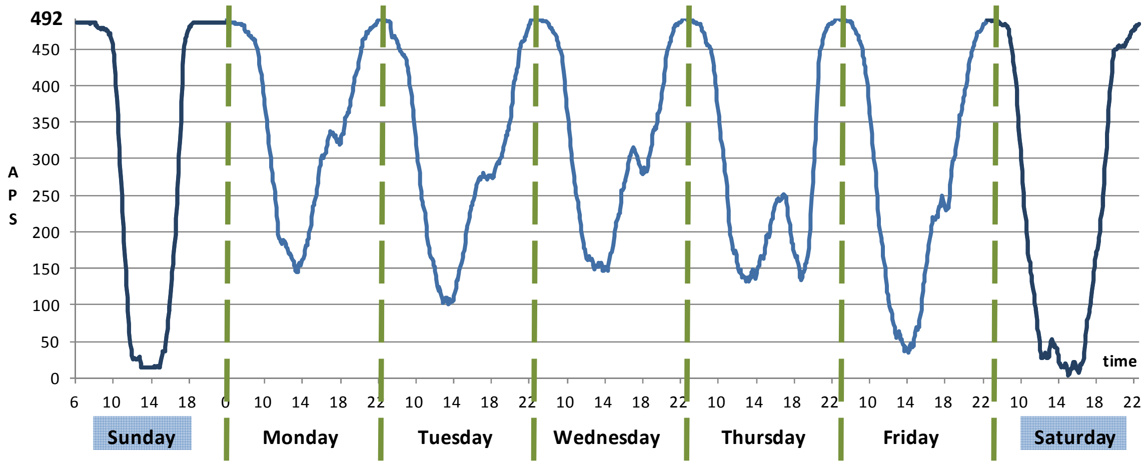

Figure 1: Weekly change curve of APS (sample data from 11-17th September 2011)

According to the values of correlation and distance, workdays are very similar while Saturdays and Sundays exhibit different characteristics. It is also reasonable in common sense that changes in APS patterns between workdays and weekends occur due to different travel purposes: people travel for work on workdays and primarily for entertainment and shopping on weekends. This pattern is also observed in the other monitored parking facilities in Newcastle, namely: The Quayside Multi (a parking building close to the central railway station), and John Dobson Street Lot (a parking facility located between several office buildings). We can also observe that although these parking patterns on Saturday and Sunday do not relate well to the standard weekdays patterns, they enjoy a high degree of similarity with data measured on other Saturdays and Sundays. According to this, we assume that when we train the forecasting models, we should deal with workdays and weekends separately.

Analyzing the data of four successive weeks from 22-8-2011 to 25-9-2011, four kinds of typical weekdays were chosen: Thursday, Friday, Saturday, and Sunday. We selected the APS of the last week (19-9-2011 to 25-9-2011, regarded as 'Week4' in table1 below) as the data base, the *r* and *d* of other data sets compared to the data base is shown in table 1.

Table1: the Pearson Coefficients and Absolute value of the difference of Three Weeks Comparing to Week4 (19th to 25th September 2011)

weekday / week	Thurs		Fri		Sat		Sun	
	r	d(lots)	r	d(lots)	r	d(lots)	r	d(lots)
Week1	0.99	29.5	0.97	34.4	1.00	14.8	1.00	9.8
Week2	0.98	19.7	0.98	34.4	1.00	9.8	1.00	9.8
Week3	1.00	19.7	0.98	24.6	1.00	19.7	1.00	9.8

As shown in table 1, the Pearson coefficients are very close to 1 for the previous three weeks, the absolute values of the difference are also rather small, although they increase as time goes on. Thus we propose that when dealing with Sunday APS forecasting, we can establish the forecasting model using the data of several previous Sundays, due to the strong Sunday-to-Sunday correlation. Moreover, Saturday's relation to the previous Saturday is not obvious (which could be due to major football match events occurring every second or third Saturday), making Saturday inappropriate for use as the training data set.

3. METHODOLOGY AND PREFERENCES

3.1 Reconstruction of phase space

The first step in the process of short-term time series forecasting is reconstructing the phase space. A method for reconstructing phase space from an observed time series has been presented by Takens [29]. The time series is assumed to be generated by a nonlinear dynamic system with *m* degrees of freedom. It is therefore necessary to construct an appropriate series of state vectors y_t with delay coordinates in the phase space:

$$y_t = (x_t, x_{t+s}, \cdots, x_{t+(m-1)s}) \qquad (3)$$

where s is referred to as the delay time and for a digitized time series is a multiple of the sampling interval used, while *m* is termed the embedding dimension.

3.2 Wavelet neural network approach

Wavelet transform (WT) is generally efficient in extracting useful information from signals. Neural network (NN) is a self-learning, self-adaptive and fault-tolerant function approximator. In 1992, Zhang Qinghua put forward wavelet neural network (WNN), which combines both WT and NN [30].

WNN is class of feed-forward neural network and has activation function of the hidden layer nodes from continuous wavelet function [31, 32]. In this paper, the WNN is based on the BPNN which has three layers named input layer, wavelet layer and output layer[33]. The structure of WNN is shown in Figure 2.

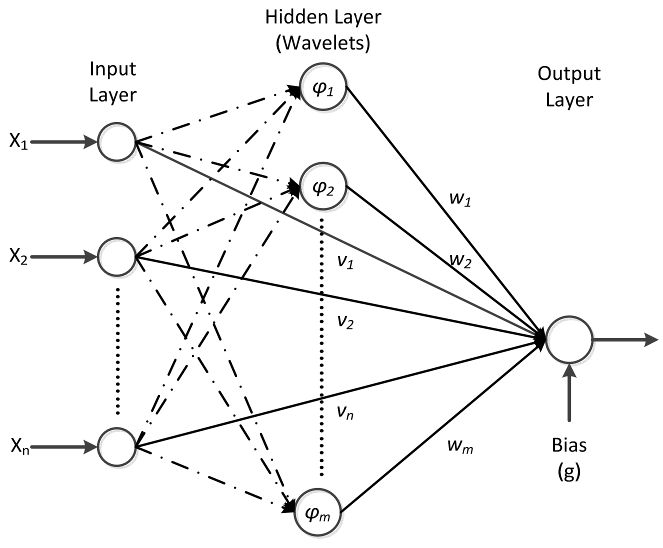

Figure 2 Structure of wavelet neural network[33]

The input data vector is firstly transmitted to the wavelet layer. In this process, the mother wavelet function plays an important role. It can be changed into wavelet bases by scale *a* and shift *b* operations. It can be expressed as:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \qquad (4)$$

Usually, in forecasting applications, input data should be transmitted to feed the forecasting model, therefore, multi-dimensional wavelet function should be built as given by：

$$\varphi_j = \prod_{i=1}^{n} \psi_{a_{ij}b_{ij}}(x_i); j \in m \qquad (5)$$

Where $\mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, \cdots, \mathrm{x}_\mathrm{n})$is a n-dimensional input vector, m is the number of neurons in the wavelet layer, a_{ij} and $b_{ij}$are parameters.

Taking all the connection from input to output nodes into consideration, the final output of the WNN can be computed as:

$$y = \sum_{j=1}^{m} w_j \varphi_j + \sum_{i=1}^{n} v_i x_i + \mathrm{g} \qquad (6)$$

Where w_j is the layer weight between the ***j***th node of product layer and output node, v_i is the input weight between ***i***th input variable and output node, and g is the bias of output node.

3.3 Preferences of WNN

The fundamental parameters of WNN are set according to previous studies where they have been fully researched [34, 35]. We use the Morlet function as the mother wavelet function and select optimal numbers of the hidden nodes by experiment according to different number of input nodes. Morlet wavelet has the smallest error and the best computational stability, the formula is given below[36]:

$$\psi = \cos(1.75x) \times \exp(-\frac{x^2}{2}) \qquad (7)$$

However, there are not conventional methods concerning the selection of preferences in time series prediction field, such as the delay time and embedding dimension. Thus these are discussed along with the choosing of an optimal training data set in this section.

3.2.1 Determine the optimal train sets

The data set we used to train the WNN weighs heavily in the forecasting process. Without altering the network, the change to a reasonable training set can notably promote the accuracy. On the other hand, the size of the training set also influences the veracity and efficiency.

We set the interval to 1min to process the original data and recorded unoccupied parking space data in 1440 intervals for a day. Furthermore, when we only pay attention to hours with meaningful information that is 6:00 to22:00,the intervals are reduced to 961. The APS data of September 16, 2011(Fri.) is chosen as the test set, data of Monday 12th to Thursday 15th September and Wednesday 7th to Friday 9th September 2011 are selected as an alternative training set. We set the training set from one day data (961 intervals) to seven days data (7*961 intervals), one day as the minimum interval, that is in all seven different sizes of training sets on which we train 80 WNNs to eliminate random error. The standard error and total time spent (the sum of training and testing time, the program is calculated in MATLAB 2010a without other programs running, the CUP is Intel i5-2430) curves are shown in figure 3.

We can observe from figure 3(a) that the average standard error line is basically constant when the training set size is more than two days, and that the standard deviation is also considerably lower between 2 to 4 days. In addition, when the training set is chosen as six or seven days, the prediction error rises abnormally because over-fitting of the training set may lead to low prediction accuracy for the test set. Combined with the time spent tendency shown in figure 3(b), we consider two or three days' data to be the optimal training set size.

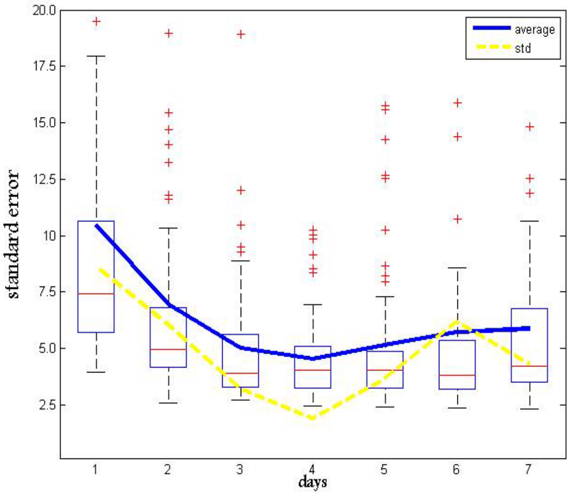

FIGURE 3(a) Standard Error Curve.

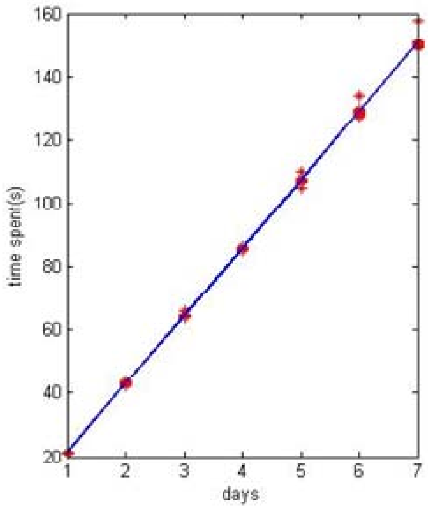

FIGURE 3(b) Total Time

The most unfavorable condition in the APS forecasting process is the prediction for Sunday as it has the lowest coefficients compared with other days. As analyzed above, we have two strategies for weekends: one uses the previous three days' data as a training set, represented by Tactic 1; the other uses the previous one day plus the same days from the previous two weeks, represented by Tactic 2. Choosing the data of September 18, 2011 as a test set for the example, the first tactic's straining set includes September 17, 16 and 15 while the second tactic's includes September 17, 11 and 5. After 80 trials of running each tactic, their performance is shown as bellow:

The average MSE of Tactic 1 is 11.6 while Tactic 2's is 7.0, thus including the same weekday's data a week before in training set has improved the weekend APS predicting performance when dealing with special days. Meanwhile, as the forecasting becomes steadier: the standard deviation improves from 8.7 to 4.4 as well.

3.2.2 Determining the optimal delay time and embedding dimension

Optimal delay time (*s*) and embedding dimension (*m*) can be directly computed using the largest Lyapunov Exponents (LEs) methods. However, there isn't sufficient evidence that we can use the same result in WNN, for these two methods are intrinsically different.

Experiments were conducted to find the optimal *t* and *m*: The APS data of September 16, 2011(Fri.) is chosen as test set, data of Tuesday to Thursday (13^{th} to 15^{th} September 2011) respectively are selected as training set. For every different delay time and embedding dimension value we train 80 WNNs to eliminate random error where the delay time embedding dimension ranges from 1to 10 and 1to 20 respectively. The selection of the range is based on former study, though expanded to a larger extent. The average standard error and total time spent curved surfaces are shown in figure 4.

After analyzing the figure, we get preliminary conclusions that we can achieve both accuracy and efficiency when $s+m<13$. Furthermore, detailed MSE information can be achieved from the experiment data in this rather efficient (s, m) region: there is a slight decline from 9.3 to 6.4 when m changes 1 to 2 and then the MSE remains stable. In addition, the lowest MSE (5.4) is achieved when $s=1$, $m=3$.Thus we recommend the area where $s+m<6$ and $m>1$. In the remaining sections of the paper, the delay time and embedding dimension are set as 1and 3 for all WNNs.

4 SHORT-TERM APS FORECASTING

The research was conducted by experiments involving short-term APS forecasting, where the prediction performance of WNN and LEs method are compared in the aspects of accuracy, efficiency and robustness.

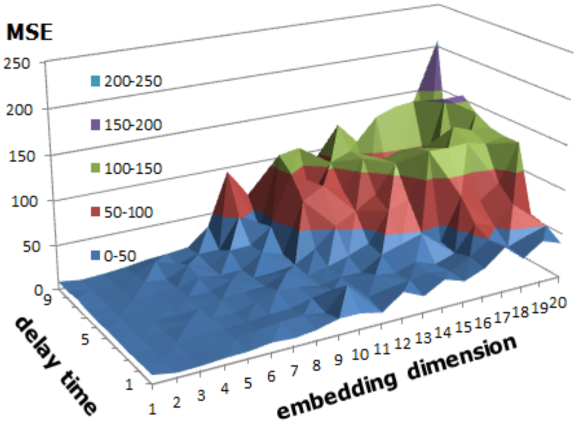

FIGURE 4(a) Standard error surface plots.

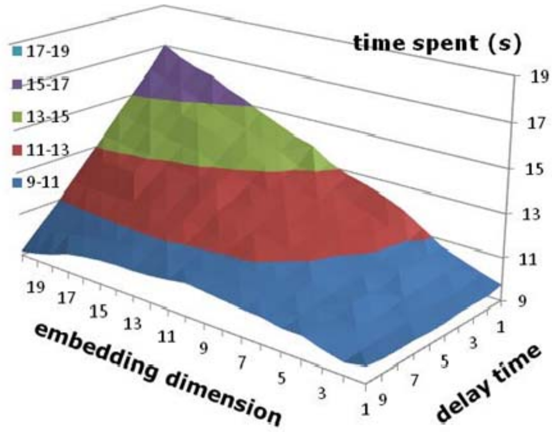

FIGURE 4(b) Time spent surface plots.

4.1.1. Prediction accuracy and efficiency

➢ **Experiment 1:** Following the optimal training set choice strategies above, we used a three-day based training set (Tuesday 13th to Thursday 15th September 2011), with the Friday 16th September as the test set, and the time interval set as 1 or 5 minutes. All the algorithms described in the previous section use these training data to predict APS. Since the link weights in neural network are randomly chosen, we did both 80 experiments for ANN and WNN to eliminate the impact of random error. The differences between observed APSs and predicted ones are shown in figure 5(a), with a time interval of 5 minutes. The central goal of Experiment 1 is to compare the accuracy and efficiency of two algorithms.

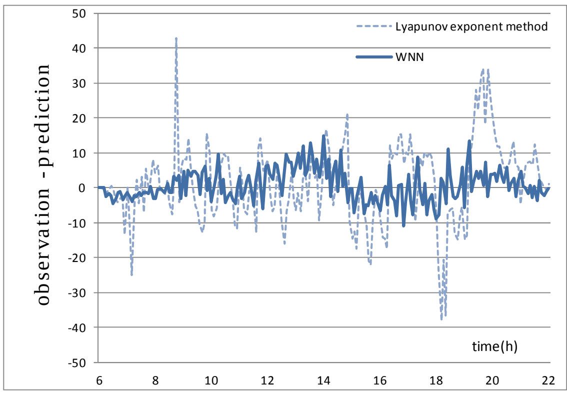

FIGURE 5(a) Difference between observed and predicted values for normal days.

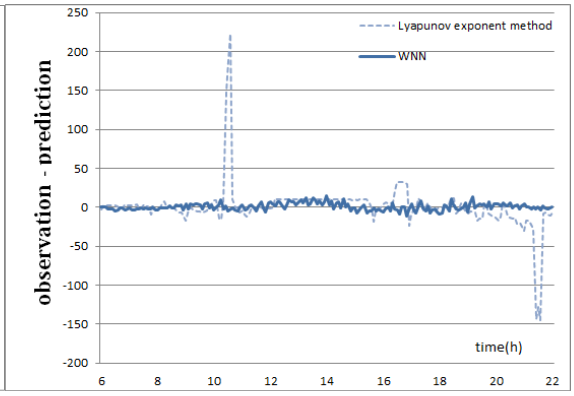

FIGURE 5(b) Difference between observed and predicted values for holiday days.

➢ **Discussion 1:** The average standard error is the honest estimate of the true error extent, which is also an indicator of how good the network is. In this extend, the WNN appears obviously more accurate with an average standard error of 6.4±3.1, compared with18.7 for the largest LEs method. What's more, WNN has a more rapid speed in forecasting process as the average time spent for WNN and largest LEs method are 13.3s and 29.7s for 5minutes interval, and 63.9s and 42minutes for 1minute interval, respectively. Therefore we conclude WNN achieved a more precise and efficient performance in one-step forecasting APS of normal days.

Further analysis of the time spent suggested that in WNN's 5-minutes-interval forecasting the whole 13.3s consist of 13.1s network training time, which only need to be conducted once a day during off-peak (slack) hours. The remaining 0.2s forecasting time equals 0.001s for per prediction step, which remains the same computational cost in 1minute prediction. By comparison, every time slot takes 0.15 s to be forecasted in largest LEs method; this rises to 2.61s when the time interval becomes 1minute. Thus WNN is a better choice for short-term APS forecasting due to its infinitesimal time delay in dealing with small forecasting intervals.

4.1.2. Performance in abnormal data prediction

APS is a rather uncertain quantity for it changes under volatile circumstance. Some 'big' events, such as Olympic Games or Christmas sales, will cause the APS to stay at a high level all weeklong, which we call abnormal data. Yet these data need particularly accurate forecasting due to the rather acute tension between parking lot supply and demand.

- **Experiment 2:** To investigate the volatile situation, a week before Christmas 2011 is analyzed as Newcastle is a major regional shopping centre with significant increases in footfall and traffic in the weeks before Christmas. The parts of APS of this week and a week before is shown in figure 5(c).The ratios on December 19^{th} and $20^{th}$are constantly high and change abruptly from the data from 14^{th} to 16^{th} December. These tendencies may lead to different performance of the forecasting algorithm compared to normal days. We set the data of December 14^{th} to 16^{th}as training set (a normal training set), with Dec. 14^{th} as testing set (an abnormal test set), and then train 80 networks of WNN and the largest LEs model on these data. The central goal of Experiment 2 is to compare the ability of two methodologies to deal with an abnormal test set that has low correlation coefficients with previous data.

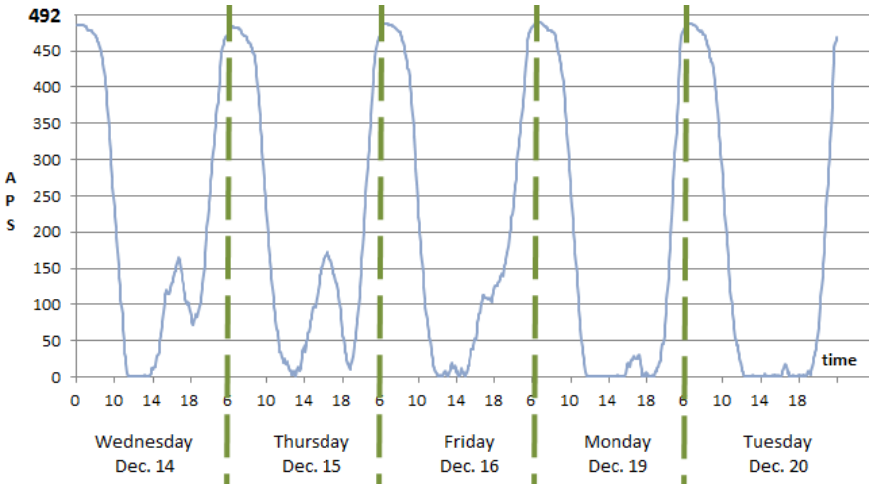

FIGURE5(c) APS from 14^{th} to 20^{th} December 2011

- **Discussion 2:** According to figure 5(b), the standard error in forecasting using WNN, ANN and largest LEs method is 9.8%±3.5% and 31.0, respectively. It can be observed that among 10:00 to

11:00 and 21:00 to 22:00 when the APSs increase and decline suddenly, the error of the largest LEs method abruptly increases on account of falsely applying the pattern of the normal data to abnormal test data. The same phenomenon occurs in weekend APS prediction where MSE of WNN is 8.7%±6.2% compared to largest LEs method a 29.0 MSE. Therefore, the largest LEs method is inadaptable for abnormal data forecasting, and we advocate using WNN instead.

5 CONCLUSION

The paper has utilized parking data from several large parking facilities in Newcastle upon Tyne, England and associate traffic and flow data provided by the Tyne and Wear UTMC system to investigate improvements in algorithms to estimate available parking spaces.APS forecasting techniques are a crucial research topic of PGIS, whose prediction accuracy directly impacts guidance effectiveness and the acceptance of such systems by drivers. The paper has presented research which aimed to find the optimal predicting method, considering WNN and the largest LEs method, which were compared and verified from the observed APS data from Newcastle. To investigate the most optimal method which could provide sufficient PGIS, short-term APS forecasting, covering 1 or 5 minutes (determined by the value of time interval)was researched for the two methods and their performance compared by prediction experiments. The main findings are listed as below:

- In short-term forecasting of workdays' APSs, setting the time interval as 5minutes, WNN performs better with a lower average MSE of 6.4±3.1, compared to the largest LEs method whose MSE is 18.7, and with less than half the computational cost as 13.3s for WNN to 29.7s for the largest LEs method. As the time interval decreases to 1minute, the increasing APS information leads to a sharp rise of the largest LEs method's time spent which increases to 42minutes while remaining much lower at 63.9s for WNN. Therefore we conclude that WNN is more appropriate to be applied to workdays' one-step APS forecasting for its precision and low time delay.
- The prediction of APS among holidays and weekends requires specific research due to the acute imbalance of parking demand versus supply and the weak relationship between the previous days' data and these 'special' days. After studying the characteristics of APS in terms of correlation coefficient and average distance, we suggest including the same weekend days of the previous weeks (or the same holiday period of the previous year) into the training set. This practice improves the average MSE from 11.6±8.7 to 7.0±4.4 for WNN forecasting. Meanwhile the largest LEs method appears unable to precisely forecast these special data due to high MSE of 29.0 for weekends and 31.0 for holidays APS predicting.
- The calculation of the optimal delay time (s) and embedding dimension (m) are well studied in chaos theory based short-term time series forecasting, but seldom referred to when other methods are applied such as WNN. After experiments and observation, we recommend the area where $s+m<6$ meanwhile $m>1$, which leads to both accuracy and efficiency in WNN based short-term APS forecasting.

In summary, we have shown that WNN is an appropriate method for short-term APS forecasting in both weekdays and weekends. This accurate and efficient method can provide sufficient and timely information for the travelers' decision-making, while contributing to the parking guidance system.

However, because of the limitations of the survey data and the algorithm, the research has several aspects to be improved in the future:

- This paper focused on time series predictions; we did not consider the influence of factors such as characteristics of drivers' behavior in choice making and environmental situations.

- The conclusion is drawn mainly by comparison and experiment which can be improved by conducting theoretical analysis of the intrinsic features of the compared algorithms.

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