EFFECTS OF WEATHER CONDITIONS ON BICYCLE DEMAND IN DUBLIN

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ABSTRACT

Cycling is being actively promoted in recent times as a sustainable alternative to motorized travel. To efficiently promote cycling in a multimodal urban transport network, it is important to manage the bicycle demand similar to other major modes of transport such as, passenger cars or public transport. For a successful management of bicycle demand, specific to each network, a comprehensive understanding of the key participating variables is required. In this context, it is crucial to analyse the variability of bicycle demand with respect to variable weather conditions and within-day-variability, since these are considered to be key markers responsible for the temporal variation of the demand. A quantitative understanding and evaluation of these markers help developing network-specific predictive bicycle demand models.

Keywords: Cycling, forecasting.

INTRODUCTION

Dublin like many other international cities is currently experiencing an increase in cycling. Dublin is the capital city of Ireland and has a population of 1.2 million (CSO, 2012). The topography of the city is relatively flat which makes it an ideal candidate city for cycling. Dublin has a mild climate with on average 61mm of rain per month. This compares with 64mm in Amsterdam, 44mm in Copenhagen and 78mm in Freiburg, all cities with a traditional reputation of being the most cycle friendly cities in the world (World.Climate.com, 2012). Given the climate and topography of Dublin it is an ideal candidate for growth in cycling rates.

In 2009, the Irish Department of Transport published two documents, the National Sustainable Travel Policy and the National Cycle Policy Framework (Department of Transport 2009a, 2009b). Both documents set out goals for increasing the modal share of cycling and the development of cycle lanes and the promotion of cycling using marketing and promotion events. One such policy was the introduction of tax-free loans to purchase bicycles. Figure 1 shows the results from the annual cordon counts taken in Dublin from 1997 to 2012 (Dublin City Council, 2012). The results show that since 2004 that there has been a steady increase in the numbers cycling into the city. These cordon counts are undertaken in November each year and as such may be subject to seasonal effects and the true cycling numbers in the city may be higher.

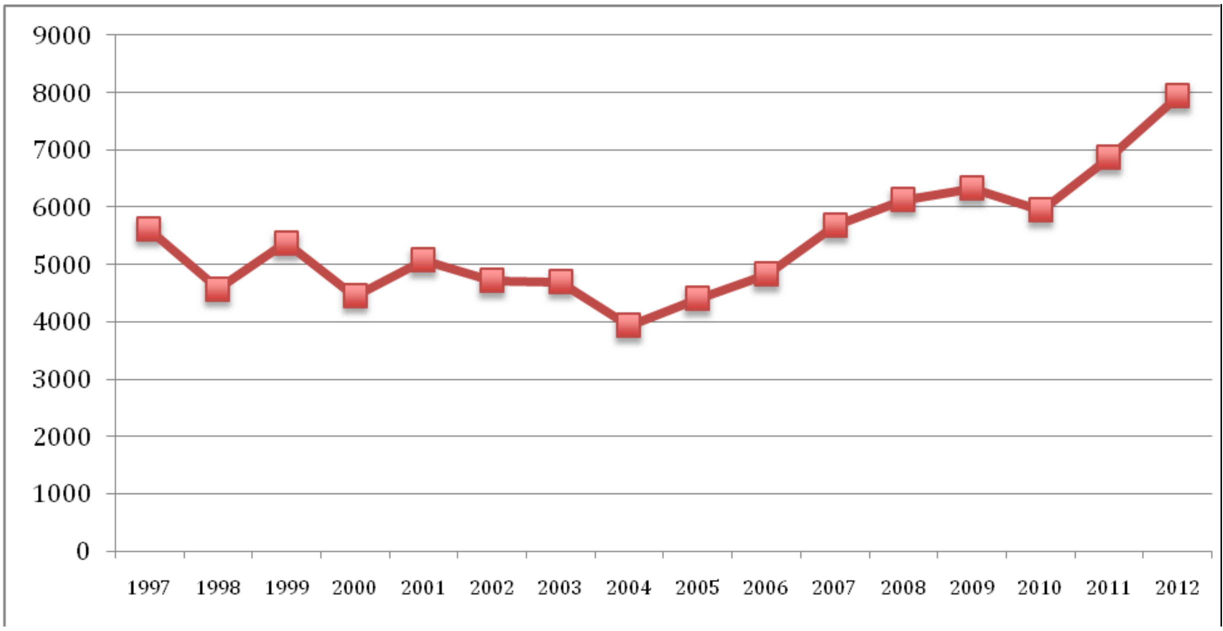

Figure 1 Growth of cycling in Dublin

To accommodate this increase in cycling several cycle lanes have been constructed in the city. This paper examines the usage of one such cycle lane using counter data that was collected to examine what impact weather has upon cycling rates in Dublin.

CYCLIST VOLUME AT RECODING STATION

24 hour cycle flows on an urban, on-road bike lane and a suburban segregated bike lane is collected in Dublin, Ireland. The in-bound and out-bound demands at the locations are studied separately to estimate the temporal variations of the demand in either direction (see Figure 2 for a map of the survey site). The datasets are analysed using time-series models and predictive algorithms are developed to predict the bicycle demands at both locations. Also, a multivariate analysis (principal component analysis) is performed to estimate the influence of weather conditions (temperature, daylight hours, rainfall etc) on bicycle travel demand.

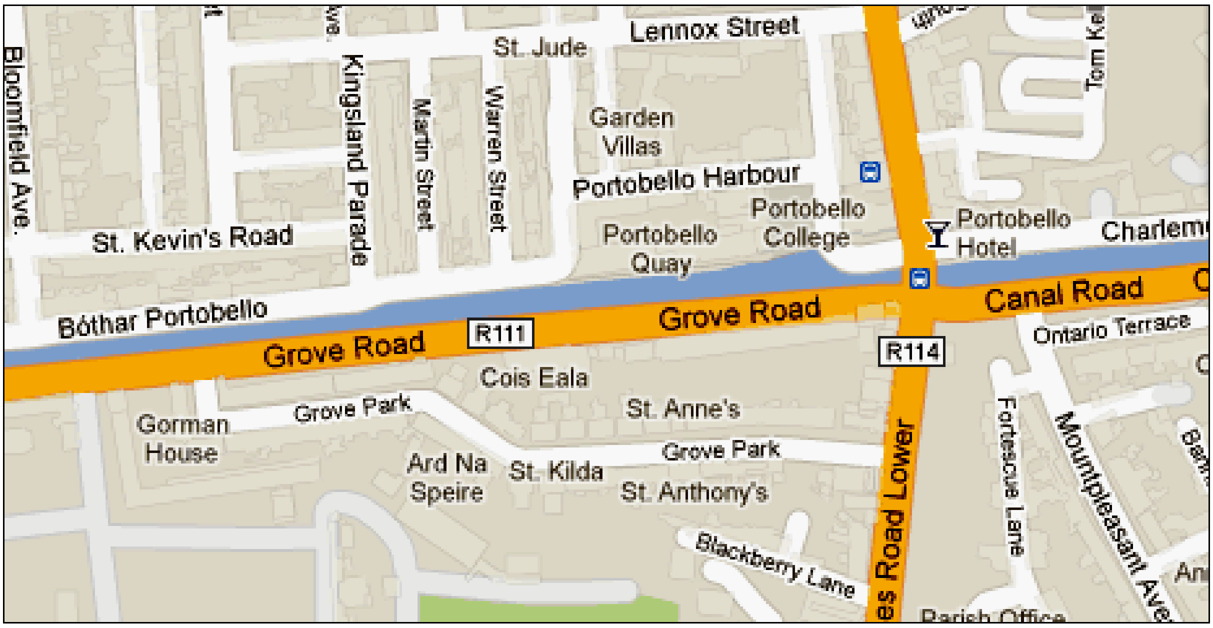

Figure 2 Map of Site (https://maps.google.ie/)

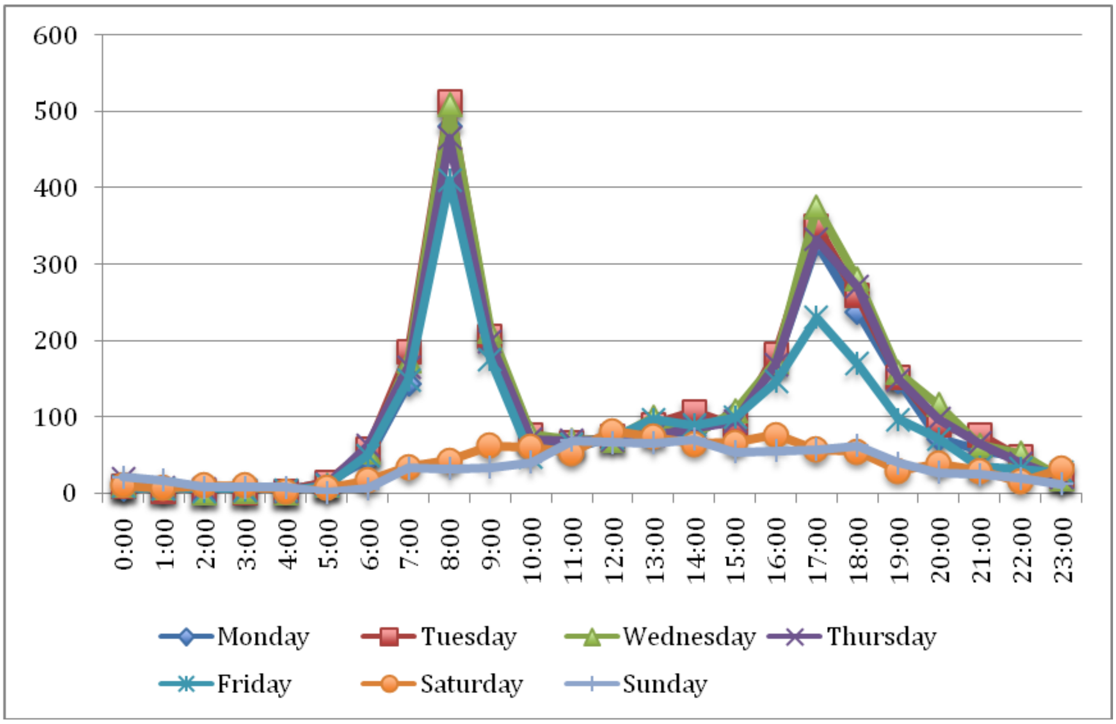

Figure 3 Cyclist volumes in weekdays and weekend

Figure 3 shows similar to vehicular traffic, cyclist volume drop and show a different dynamics during weekends compared to weekdays. This is due the absence of commuter cyclists during weekends. As the weekend travel behaviour of cyclists is very much unlike the travel behaviour in the weekdays, the modelling is essentially carried out on the data observed during weekdays. Considering the regularity of behaviour, it is a regular practice to model weekday traffic behaviour ignoring the weekends (Ghosh et al. 2007, 2012). Hence, weekday commuter cyclist volume has been modelled for forecasting purposes in this paper. Since, the data set used does not contain any missing data, no special treatment for missing data is required to be utilised here.

DATA ANALYSIS

For the purpose of time-series modelling, the data were analyzed for getting an overview about the characteristics of the series. The software MINITAB 16 was used to calculate the statistical functions required in the paper.

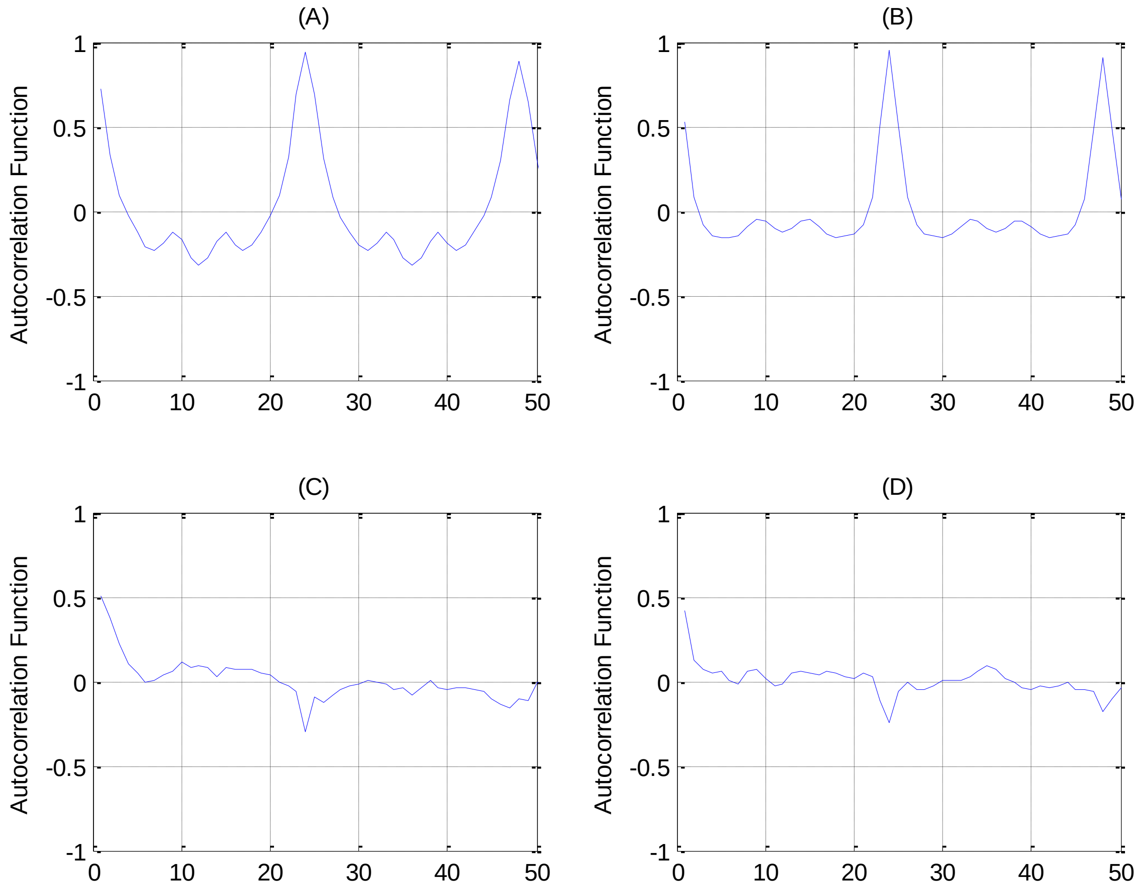

Figure 4 Autocorrelation plots of cyclist volumes (inbound (A) and outbound (B)) and differenced cyclist volumes (inbound (C) and outbound (D))

To convert the traffic flow data series to a zero-mean sequence, the mean was subtracted from each observation. The zero-mean process or the centred traffic data was to be processed further to make it 'stationary' in nature. In this paper 'stationary' means 'second-order stationary'. A correlogram of the centred data is plotted in figure 4 (A & B). The correlogram shows that the Auto-Correlation Function (ACF) has considerably large values repetitively, after a particular interval of time. The ACF is very much like a sine wave with a time period of 24 observations. This is a clear indication of the seasonality of the data.

From the correlogram it is quite evident that the zero-mean process is also non-stationary in nature. As the series is seasonal in nature, a seasonal difference was taken to remove this non-stationary. The correlogram plot of the seasonally differenced cyclist volume data plotted in figure 4 (C & D) show that the ACF values drop to zero (i.e. within the limiting lines) rapidly. Hence, the series became stationary in nature. The stationary cyclist flow data was then modelled using a Seasonal Autoregressive Moving Average (SARIMA) model.

If the time-series data to be fitted in an ARIMA model has some intrinsic seasonality, then instead of simple ARIMA, a seasonal ARIMA model can be used. There are two types of seasonal models, additive and multiplicative. Here the multiplicative SARIMA model (p, d, q)(P, D, Q)s is used. In the multiplicative model the non-seasonal part (p, d, q) and the seasonal part (P, D, Q)s part are multiplied together. P & p indicate the order of autoregressive processes, Q & q indicate the order of moving average processes and d the order of difference and D is the order of seasonal difference. The cyclist data was used for ARIMA modelling using Box and Jenkins (1970) methodology.

SARIMA $(1,0,1)(1,1,1)_{24}$ was found to be the most suitable model for predicting the hourly cyclists volume over a day both inbound and outbound traffic. To evaluate the efficiency of the models, 24 points in the future are forecasted for both inbound and outbound series. The observations obtained on the 25th November 2011, or data collected in next 24 hours are compared with these forecasts. The SARIMA$(1,0,1)(1,1,1)_{24}$ model forecasts along with the original observations are plotted in figure 5 & figure 6 for outbound and inbound cyclist volumes respectively. Only the point forecasts are considered in each case and the prediction intervals are not employed.

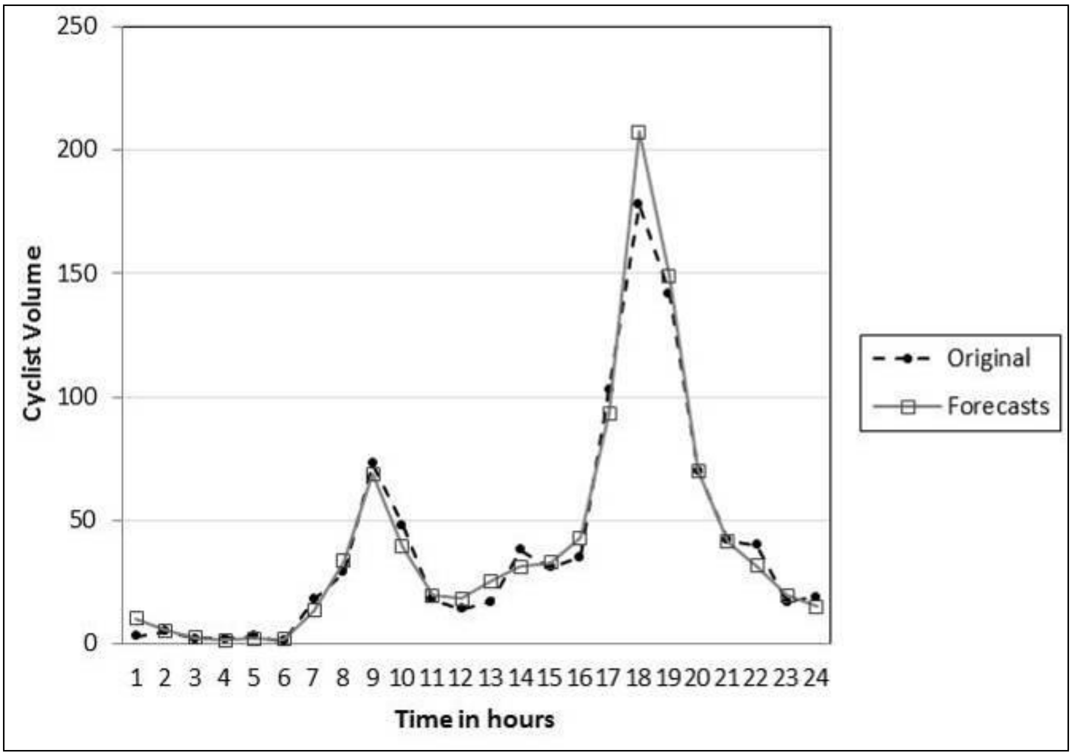

Figure 6 Observed and predicted outbound volume of cyclists

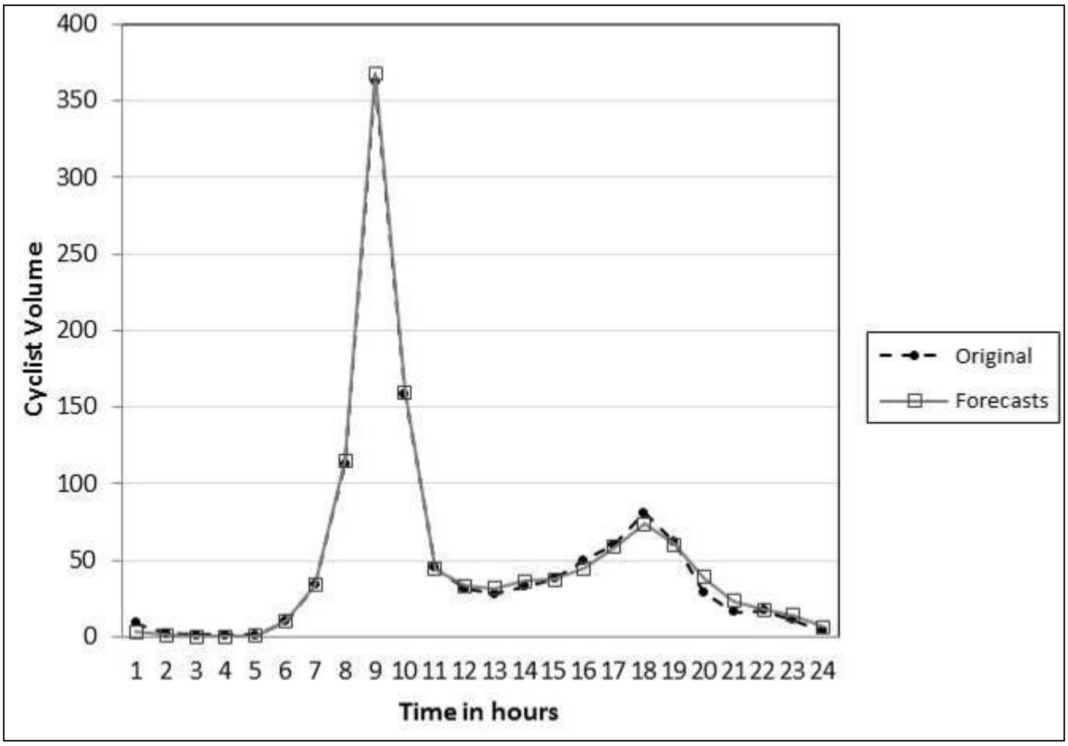

Figure 7 Observed and predicted inbound volume of cyclists

The Mean Absolute Percentage Error (MAPE) for inbound traffic over a day was 19.8% where for outbound traffic it was 19.7%. The models provided much better prediction accuracy during the peak hours. For morning peak hours the inbound model generated an error of 12.3% and the outbound model generated an error of 6.6%. The SARIMA models have a tendency to predict more towards the mean and cannot take into account of the extreme values very well. Hence, the errors are much bigger during the off-peak hours, whereas during the peak hours the models perform considerably well. This essentially can be a very useful tool to predict cyclist volume in near term future during rush hours. This will help in altering traffic signal at junctions with high volumes cyclists in real time as is done for vehicular traffic through real time adaptive traffic control system.

The weather data in relation to the movement of cyclists were analysed next. The outbound and the inbound traffic were compared against the rainfall (mm), wind speed (kt), mean wind direction (degree) and the temperature (^{o}C) from 1st October,2011 midnight to 1st October, 2012, 11pm. The scatter plot of cyclist volume is presented with weather data is presented in Figure 8.

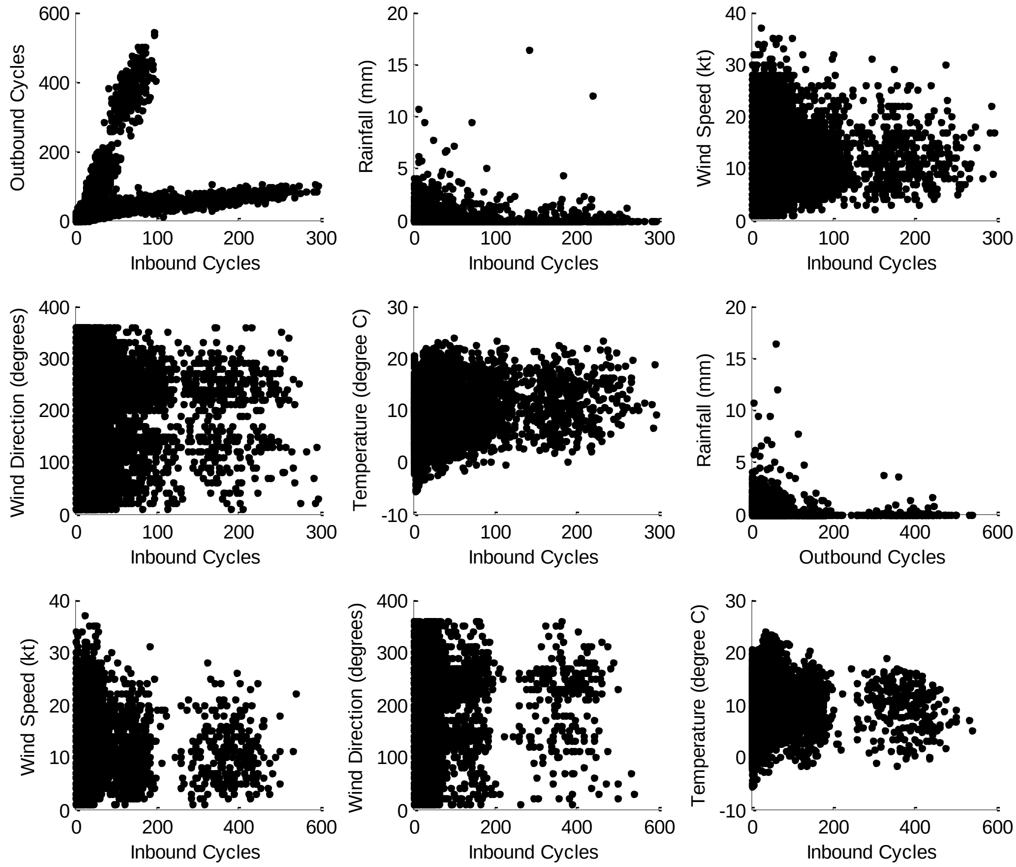

Figure 8. Scatterplot of variables measured with respect to the flow of cycles

The correlation with the outbound cycling numbers with the inbound numbers, rainfall, wind speed, wind direction and temperature are 0.3496, 0.0339, 0.0636, -0.0434 and 0.1560 respectively. The inbound and the outbound flows show two separate regimes of linear relationship. However, the correlations are not appropriate to indicate the interrelationships of variables, relative rankings and explanation of variance within data. Additionally, it is not possible directly to interpret these low correlations in terms of their influence on the data.

A principal component analysis is carried out on the collected data. The accumulated weather data are independent and limited. However, a principal component analysis can explain the percentage variances related to the components involved in the process. Figure 9 presents the scree plot for the measured weather components.

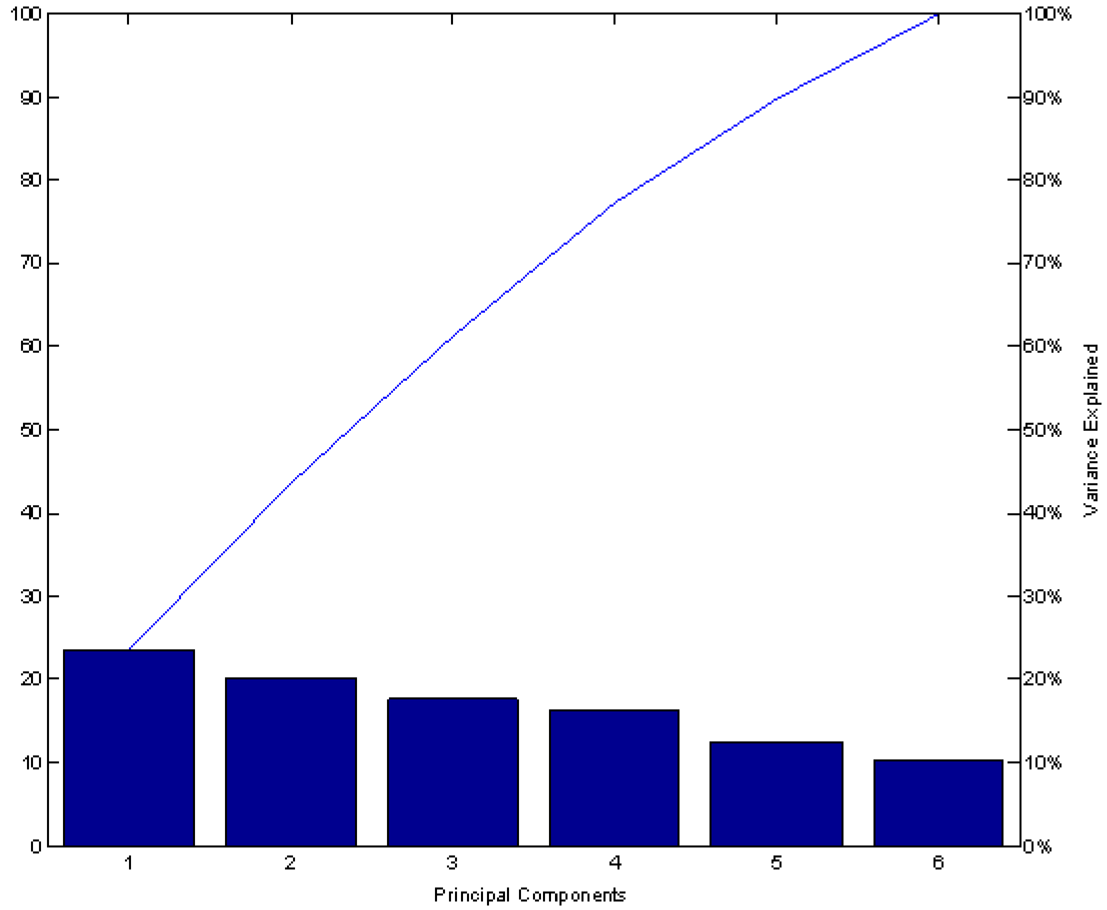

Figure 9. A scree plot of the variables involved in the flow of cycles with percentage variance explained.

Variables	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6
Outbound Traffic	0.68	-0.15	-0.08	-0.01	0.09	0.71
Inbound Traffic	0.59	-0.23	-0.36	-0.23	-0.08	-0.64
Rainfall	0.12	0.19	0.59	-0.74	0.22	-0.05
Wind Speed	0.08	-0.55	0.59	0.18	-0.56	-0.05
Wind Direction	-0.21	-0.70	0.02	0.00	0.68	-0.04
Temperature	0.36	0.31	0.41	0.61	0.40	-0.28

Table 1. Loading of each variable involved in cycling flow against percentage each principal component.

A factor analysis in this case is perhaps not advisable since a variable reduction is difficult and the chosen principal components have comparable contributions to explaining variance. However, the coefficients forming the vector of components may be looked at. Table 1 presents these coefficients or loadings against percentage variance explained for each component. To bunch weather factors correctly with other influencing variables, existing or future surveys and databases may be combined with these observations.

CONCLUSIONS AND DISCUSSION

Bicycle volumes have been modelled in this paper using time-series analysis with reasonable accuracy. This is similar to applications on car-flow, where a significant number of publications are in place. The predictive algorithm presented in this paper can be considered while modelling traffic signal for cyclists. Consideration of design based on predictive modelling of bicycle demand will enhance the objective of integrating bicycle as a major mode in a transportation network.

Investigation into the effects of weather are important to establish that moderately inclement weather conditions do not affect bicycle demand significantly; however, good weather and long daylight hours significantly influence the demand. The measured weather data explains the variances in the cycling data with comparable influence for each component. Simple correlation analysis is not appropriate to interpret or quantify the interrelationship of cyclist flow with the weather variables. The bunching of these elements can be appropriately carried out through a factor analysis integrated with existing survey and databases along with future ones.

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