Travel time prediction on signalised urban arterials by applying SARIMA modelling on Bluetooth data

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Abstract

Travel time prediction has long been the topic of transportation research. But most relevant prediction models in the literature are limited to motorways. Travel time prediction on arterial networks is challenging due to involving traffic signals and significant variability of individual vehicle travel time. The limited availability of traffic data from arterial networks makes travel time prediction even more challenging.

Recently, there has been significant interest of exploiting Bluetooth data for travel time estimation. This research analysed the real travel time data collected by the Brisbane City Council using the Bluetooth technology on arterials. Databases, including experienced average daily travel time are created and classified for approximately 8 months. Thereafter, based on data characteristics, Seasonal Auto Regressive Integrated Moving Average (SARIMA) modelling is applied on the database for short-term travel time prediction.

The SARMIA model not only takes the previous continuous lags into account, but also uses the values from the same time of previous days for travel time prediction. This is carried out by defining a seasonality coefficient which improves the accuracy of travel time prediction in linear models. The accuracy, robustness and transferability of the model are evaluated through comparing the real and predicted values on three sites within Brisbane network. The results contain the detailed validation for different prediction horizons (5 min to 90 minutes). The model performance is evaluated mainly on congested periods and compared to the naive technique of considering the historical average.

Keywords: Travel time prediction, SARIMA modelling, Arterial travel time, Bluetooth data, Time series analysis

1. Introduction

One of the most important parameters in traffic studies is travel time. Travel time estimation and prediction has long been a topic of research. Travel time estimation is transforming the observed traffic variables such as flow and occupancy into experienced travel time. Forecasting the future travel time values is termed as prediction.

To date numerous models for estimating travel time on motorways (Bhaskar and Chung, 2013, van Lint and van der Zijpp, 2003, Sun et al., 2008, Sun et al., 1999) and arterials (Bhaskar et al., 2012, Bhaskar et al., 2011, Bhaskar et al., 2010, Bhaskar et al., 2009) have been proposed. Most of the existing models on motorways are developed based on loops data, which are the oldest and widely used traffic data sources. Travel time estimation on arterial links is always challenging because of various reasons such as stop and go running conditions due to signals; non-conservation of flow due to presence of mid-link sources and sinks (e.g. parking, side street) etc. The estimated travel time is the input for the prediction modelling (Bajwa et al., 2003, Park et al., 1999).

With the advancement in technology, other data sources such as Bluetooth (BHASKAR et al., 2013, Bhaskar and Chung, 2013) and WiFi scanners (Abbott-Jard et al., 2013, Abedi et al., 2013) are being explored as a complementary transport data. Travel time from Bluetooth data is compared with that from video cameras for motorways (Wang et al., 2011) and arterial (Mei et al., 2012). This data provides significant benefit to the road operators for travel time estimation on road networks in a cost effective manner. In some studies (Haghani and Aliari, 2012), travel time from traditional matching of Bluetooth scanners is considered as ground truth travel time. Bluetooth tracking is not only being explored for car travel times estimation, but also for other applications such as bicycle travel time (Mei et al., 2012), travel patterns of people movement in airports, shopping malls (Bullock et al., 2010, Malinovskiy and Wang, 2012, O'Neill et al., 2006), work zone delays (Haseman et al., 2010), Origin-Destination studies (Barceló et al., 2012, Blogg et al., 2010, Barceló et al., 2010), route choice analysis (Hainen et al., 2011, Carpenter et al., 2012), and freeway travel time variability (Martchouk et al., 2011).

Besides collecting reliable data for travel time calculation, short term travel time prediction is a topic of interest in transport studies. This is important due to its applications in real time traffic monitoring and management, including traveller information systems. This work first estimates travel time based on Bluetooth data. Then a prediction model is applied to forecast short term future travel time values in arterial corridors. The estimated travel time from case study routes can be shown and stored as stationary recurrent time-series with a specific seasonality. Then the seasonal auto regressive integrated moving average (SARIMA) modelling is chosen to forecast future behaviour of travel time-series. This model is applied on the Bluetooth data with different prediction horizon time. The results are evaluated by comparing them with the real values. Finally, the capability of the model is tested by applying it on various corridors.

2. Background

2.1. Bluetooth data collection method

Bluetooth data application has recently become more popular in transport studies as a cost efficient method for collecting and making traffic databases in transportation studies (D. and Vickich, 2010). Each electronic device is enhanced by Bluetooth technology and used by automobile passengers, has its own unique identifier number. This number can be captured and registered by compatible Bluetooth scanners. These unique MAC (Media Access Control) addresses are captured by scanners to calculate travel time along an urban route when a vehicle containing a discoverable Bluetooth device passes through a scanner detection zone. Such a zone is the communication area defined by characteristics of the scanner antenna (Abedi et al., 2013) and here includes a radius of around 100-150 m.

Data collected and stored by Bluetooth scanners is saved in a table format and contains detailed information such as; scanner ID, captured MAC address (known as vehicle ID), detection date and time, and duration of device presence in detection zone. This data is available in databases for each detector installed along arterials. All routes in arterial networks are divided into small sections between any two continuous detectors. Then an approximate travel time is found for each vehicle ID in the specified section through matching the vehicle ID and timestamps from the scanner databases (Tsubota et al., 2011). After accumulating all the different travel times calculated from all vehicle IDs passed a specific section, an average travel time value is defined for the section. This process is done for all sections along a corridor. The entire corridor travel time value is estimated by having each section travel time within a corridor.

Estimating travel time with Bluetooth scanners along an arterial route of several links can be obtained by:

A) *Direct matching* the MAC-IDs only from upstream entrance to downstream exit of the route
B) *Time-slice* based travel time estimation from each link

An example, best illustrates the function of the Bluetooth scanners are placed at intersections A, B and C where A, B and C are in order along a route. This provides travel time estimated between any two combinations of the scanner locations. An estimation of travel time from A to C can be obtained by *direct matching* MAC-ID's at A and C. This is straight forward, but can have low sample of travel time values due to loss/gain of vehicles at B. Another approach is to first estimate time series of travel time from A to B and B to C and thereafter apply the *time-slice* based travel time estimation model on the two series to estimate travel time from A to C.

The time-slice method can be mathematically formulated as follows; consider the following variables:

- k is the time when the vehicle enters the first section;
- t_n is the entry time for a vehicle at n^{th} section;
- function $t(i, t_i)$ is the travel time for the vehicle on section i when its entry time on section i is t_i.

The time the vehicle completes its journey over the first section is given by $t = k + t(1, k)$ and the entry time at the n_{th} section is given by;

$$t_n = k + t(1, k) + \sum_{i=2}^{n} t(i, t_i)$$

The travel time estimate for the route (tt) is the sum of individual section travel times as below:

$$tt = \sum_{i=1}^{n} t(i, t_i)$$

This research applied the *time slice* method to estimate travel time along the study corridors. Figure 1 illustrates an example of a daily travel time profile along Coronation Drive, Brisbane, Australia.

Figure 1: Sample day travel time series for Coronation Dr
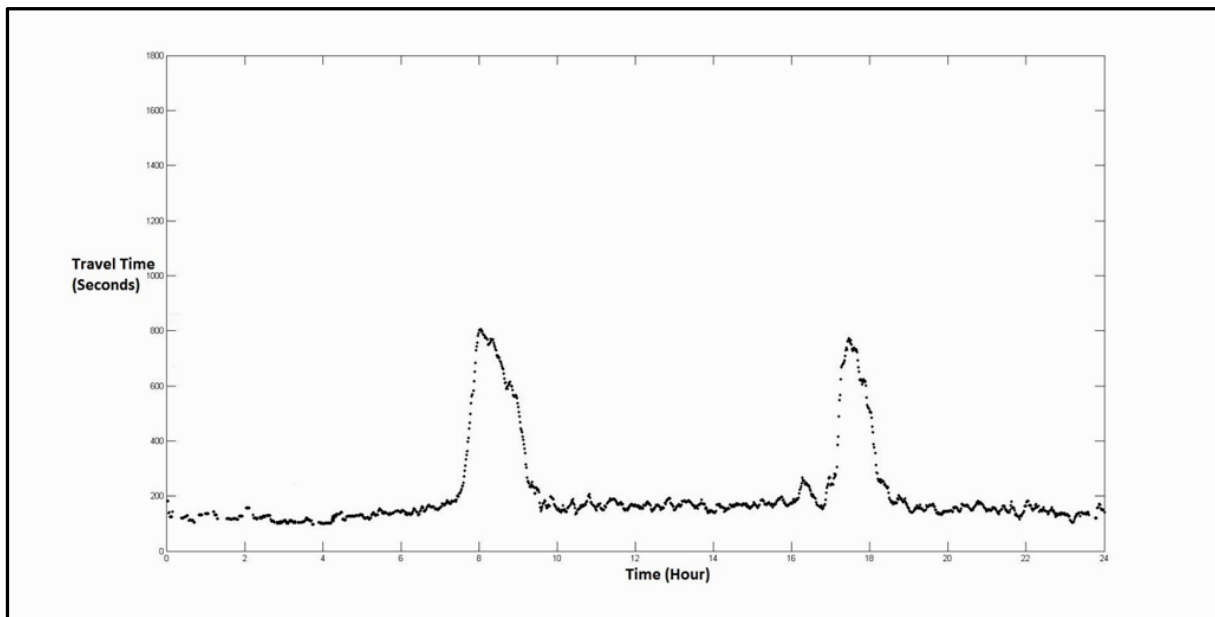
The estimated travel time values for each corridor are saved in databases which are used later in forecasting model calibration in the next steps.

2.2. Travel time prediction method

Travel time prediction is needed for a variety of ITS applications such as advanced traveller information systems, dynamic route guidance and advanced control measures. Based on the data characteristics, different methods of; historical data-base algorithm, time series models and simulations are done before for forecasting future travel time (Smith and Demetsky, 1994). Through using univariate or multivariate input data for prediction, different models have been assessed till now. In terms of multivariate data analysis, methods of linear and non linear regression, Kalman filtering and artificial neural network (ANN) are applied for predicting travel time and bus arrival time (Okutani and Stephanedes, 1984, Chien and Ding, 1999, DeLurgio, 1998). The inputs of the mentioned techniques are independent variables which have direct effects on the predicted travel time by mathematical relation based on historical data(Chien et al., 2002). There are also univariate prediction models which are designed to predict a dependent variable just by making relation between historical data and future values. The commonly used univariate models include; probabilistic estimation, time series model and ARIMA (Auto Regressive Integrated Moving Average)(Chien and Ding, 1999, Chien et al., 2002, DeLurgio, 1998, Stephanedes et al., 1990, Al-Deek et al., 1998, Anderson, 1995). Neural Network and SARIMA (Seasonal Auto Regressive Integrated Moving Average) can deal better with trends and seasonality in data (Tong and Liang, 2005). But in terms of forecasting univariate time series, SARIMA model is more suitable for short term forecasting than long term compared with neural network (Maier and Dandy, 1996). All these statements are concluded mainly for motorways, so in this paper by analysing Bluetooth data as univariate type of data, SARIMA is evaluated for the short term travel time prediction on signalised arterials as well.

2.3. SARIMA modelling

Auto Regressive Integrated Moving Average (ARIMA) method (Box, 1976) analyses stationary univariate time series. This statistical method is fitted on the data to make a better understanding of past data behaviour for predicting futures values in time series. ARIMA is a generalised model of auto regressive moving average (ARMA) method enhanced by a degree of differencing for changing non-stationary time series to stationary ones (Ong et al.,

2005). This method also becomes more useful for forecasting future values when it is fitted on seasonal time series. In this case the method is changing to SARIMA with considering a seasonality value for the historical data.

The shorthand notation SARIMA (p, d, q) (P, D, Q)$_s$ is often used when an ARIMA model is factored into "local" and "seasonal" multiplicative terms where the seasonal period "*s*" is known. The indicators *p, d* and *q* are non negative integers which refer to order of auto regressive, differencing and moving average non seasonal part of the model(Tong and Liang, 2005). Respectively the same capital letters are referring to the same action but in seasonal part.

The following equation shows the SARIMA linear mathematical formula in a general form:

$$\varphi_P(B^s)\Phi(B)\,\nabla_s^D\,\nabla^d\,X_t = a + \Theta_Q(B^s)\,\theta(B)\,a^t$$

In this equation, B and B^s denote ordinary and seasonal backward shift operators. Respectively; $\Phi(B)$, $\theta(B)$, $\varphi(B^s)$ and $\Theta(B^s)$, are polynomials (of *x* & *a* variables) in B and B^s of finite order p and q, P and Q, respectively. The "*a*" also is an estimated white noise by the model. This equation shows how much the future values are depended on their previous lags and the lags from past seasons. For example the equation for SARIMA $(1,0,1)(1,0,1)_{12}$ would be:

$$X_t = a_t - \theta_1 a_{t-1} - \Theta_1 a_{t-12} + \Phi_1 X_{t-1} + \varphi_1 X_{t-12}$$

This sample equation shows when a SARIMA model with seasonality of 12 is fitted on a historical data, the *X_t value* is predicted by making the mentioned linear formula among the previous lags in the same season and previous season (X_{t-1} & X_{t-12}), with considering a white noise and constant from current and past season.

The steps for predicting future values by SARIMA are shown in Figure 2.

Figure 2: Progress of time-series prediction by SARIMA modelling
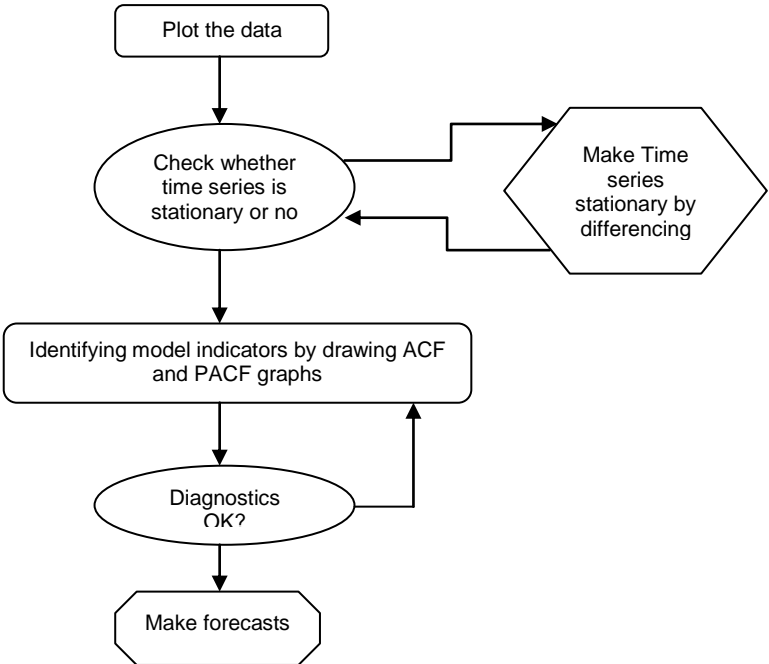

Figure 2 represents the procedure in which the first values for the *AR* and *MA* are identified by drawing ACF (Auto Correlation Factor) and PACF (Partial Auto Correlation Factor) graphs. The ACF plots the correlations between X_t and X_{t-k} against the lags (k = 1, 2, 3 …) and then identifies possible MA terms. The PACF plots the coefficients in a regression of X_t on $X_{t-1}, X_{t-2}…X_{t-k}$ and identifies possible AR terms (Reisen, 1994, Ong et al., 2005).

After this stage by fitting the model on half of data and calculating the residuals for the second half, diagnostics test is implemented. Accordingly, the final coefficients are defined and the identified model is ready for forecasting future lags.

3. Methodology

This research defines three urban signalised arterials in Brisbane. Then analyses inbound traffic flow for each. These three routes were chosen because they experience different traffic conditions in terms of; congestion periods, free flow periods and Bluetooth data volume. Travel time prediction results on these three different routes therefore provides good understanding about the model performance on signalised arterials.

The three corridors are: a) Coronation Drive; b) Wynnum Road and c) Old Cleveland Road (Figure 3).

Figure 3: Three case study corridors
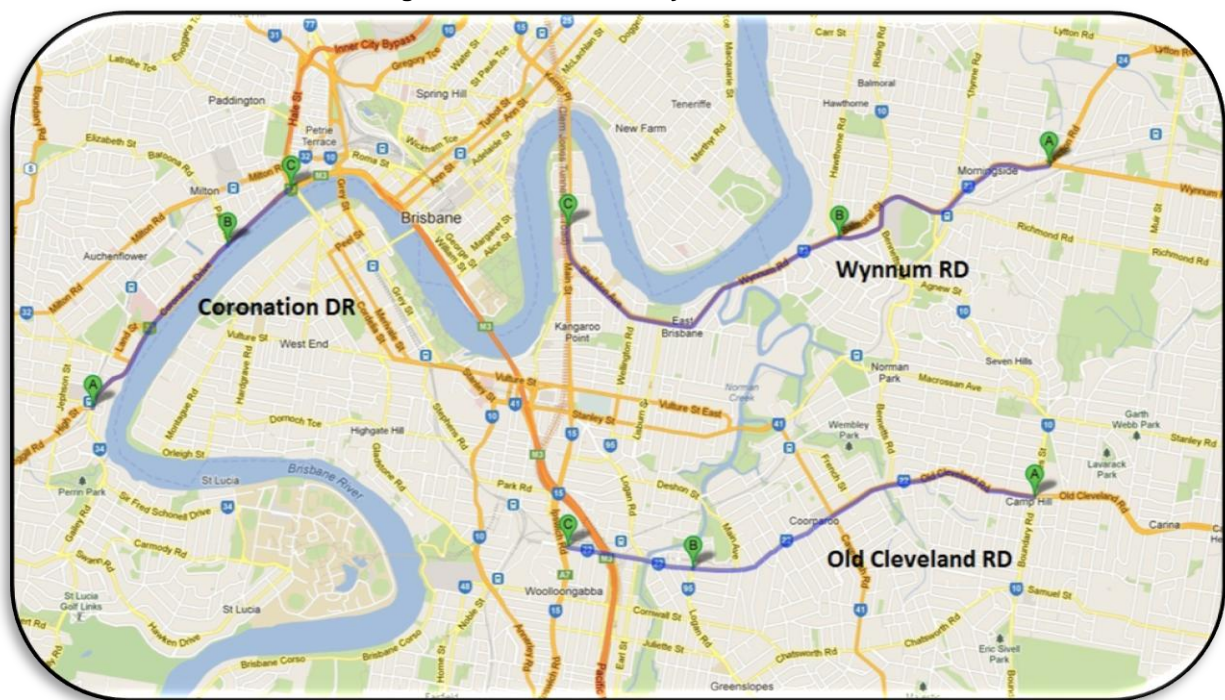
This research forecasts future travel time values based on data gathered by Bluetooth scanners installed along the defined corridors. Before developing the prediction model (Section 3.3 and section 3.4), time series of historical travel time have to be estimated from the Bluetooth data (section 3.1 and section 3.2).

3.1. Bluetooth data analyses

In this study data was collected from Bluetooth detectors installed along the urban corridors by the Brisbane City Council. This data represents unique MAC (Media Access Control) addresses captured by the Bluetooth detectors and then registered with their corresponding complete details of; date and time of first detection, and duration of presence in the detection zone. Access to this data for each detector, means the same MACs are matched from

upstream and downstream and the time spent by each vehicle to pass between the two detectors is calculated. These calculated time values between two detectors are counted as travel time for that section. This method enables several travel time values to be calculated for a unique vehicle (MAC address) in a short period of time (Araghi et al.,2010).

After calculating all travel time values for each vehicle the calculated values are filtered according to two scenarios. The first is removing multiple registered travel time values for a unique vehicle ID in a short period of time and keeping just one value. Indeed, these multiple values are caused by vehicles which exited the detection zone once and returned to it after a few minutes. After identifying the best value which represents each vehicle travel time (less than others and above a defined minimum) for a section, all values are drawn as a daily travel time series for each route. The profile *"A"* in Figure 4 shows a sample day travel time profile for a section and identifies there are extra data points with a significant difference with other points which formed a condensed pattern as a daily TT (Travel time) profile. These extra points are recognized as outliers caused by vehicles passing detectors but chosing another route for passing the distance between two detectors. They also can be generated by vehicles stopping along the way. The second scenario of filtering all outlier points is to remove them by applying MAD (Median Absolute Deviation) method (Gather and Fried, 2004).

Having travel time values as a univariate data, MAD is the median of the absolute deviations from the data's median(Gather and Fried, 2004).

$$MAD = median \mid X_i - median(X) \mid$$

$$\sigma = k * MAD$$

In this formula "k" is a constant scale factor, which depends on the data distribution. This research created a moving time window (10 minutes) for applying MAD on data. So the distribution of data in most cases is investigated as normal within the time windows. Therefore, "k" is considered as 1.4826.

By adding σ to MAD and subtracting it from MAD, a maximum and minimum margin is defined for each minute time window and only travel time values within this interval are kept as final data. The values beyond this interval are found and removed as outliers (Gather and Fried, 2004).

Profile *"B"* in Figure 4 shows how the travel time pattern looks for a sample day after removing outliers.

Figure 4: A sample daily travel time graph before and after removing outliers

| *(A)* Sample day travel time profile before filtering outliers	*(B)* Sample day travel time profile after filtering outliers
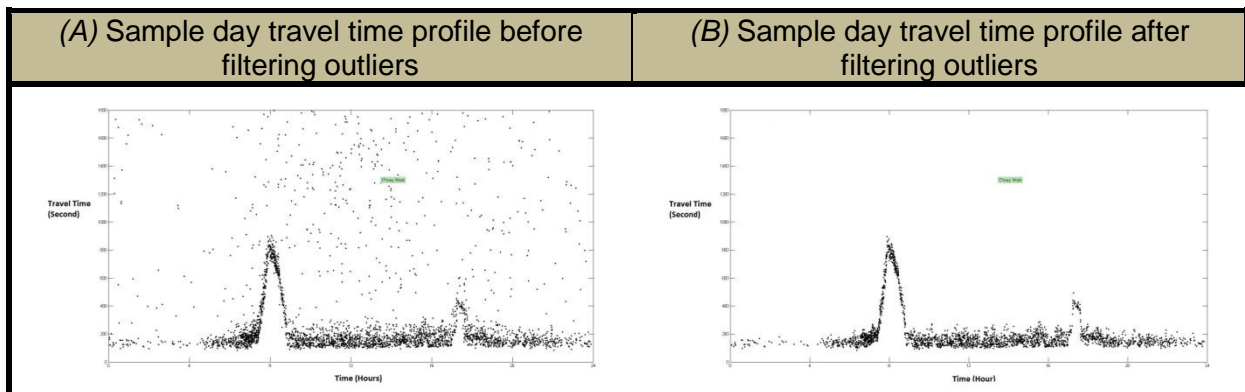
After removing outliers from each section (Distance between two continuous detectors) travel time values, the average travel time is calculated for each minutes of day by moving average method. Then after calculating TT for each minute of a day in each section, the whole corridor travel time is estimated using the aforementioned time-slice method. This process is done for all three case sample routes during 8 months from November 2011 to Jun 2012. The method of using accumulated data from all sections along a corridor, for calibrating and validating the prediction model is explained later in section 3.3.[1]

3.2. Daily historical travel time data

The next step after calculating the daily travel time value for corridors during 8 study months is to classify the data in three categories of; working days, public holidays and school holidays. Figure 5 illustrates these. Each time series in this figure represents a day travel time profile in October 2011. All graphs have the horizontal axis divided from 0 to 24 (showing 24 hours a day) and the vertical axis illustrates travel time value in seconds. This figure is a good schematic view for comparing daily travel time behaviour during a month, among the different categories.

**Figure 5: Classified daily travel time series for a sample month (October 2011)**
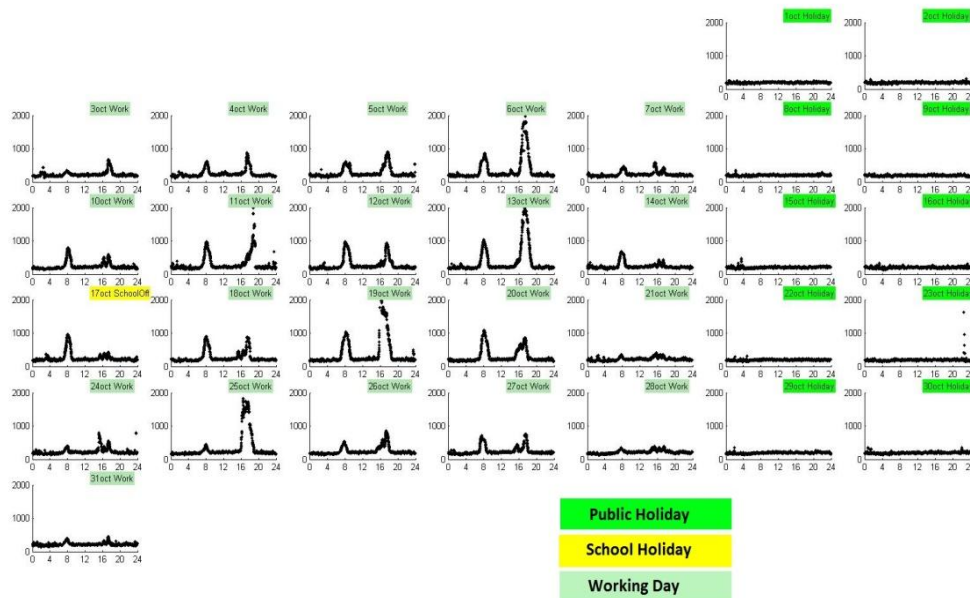
After classifying travel time data into the categories (working day, public holiday and school holiday), the similarity of daily travel time patterns is investigated by comparing the distribution of data variation during each week day. It is therefore concluded that daily travel time patterns show greater similarity on a weekly base. This means that the same week days (for example Mondays) within the same cluster (working, holiday etc.) have more similar patterns in their time series. Based on this conclusion, the historical data base for each corridor is created by putting all similar days from the same cluster, continuously together. As it can be seen clearly in Figure 5, daily travel time for working days experience more congestion (more peaks in time series) during some periods of time. So the analysis and predictions in this research are focused on the working day category.

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[1] In moving average method for estimating travel time for each minute of day, it is assumed that there are enough data points in sample sizes and TT estimated from Bluetooth data has enough confidence.

Calculating daily travel time values and putting all time series from the same cluster together identified that some days in the same cluster have unusual patterns and do not follow the routine trend. For example, in these days an exaggerated peak time can be observed, or an unexpected congestion happened during ordinary non congested hours (like during noon hours with free flow). This is further investigated by integrating the travel time profiles with incident records, and all the days with incidents (such as accidents, road works, and rainy weather) are removed.

Following these steps, the developed travel time database is ready for use in SARIMA modelling. Figure 6 shows a sample historical database for all working recurrent Mondays (19 days) before a Monday on Coronation Drive.

Figure 6: A sample historical data-base for using in SARIMA
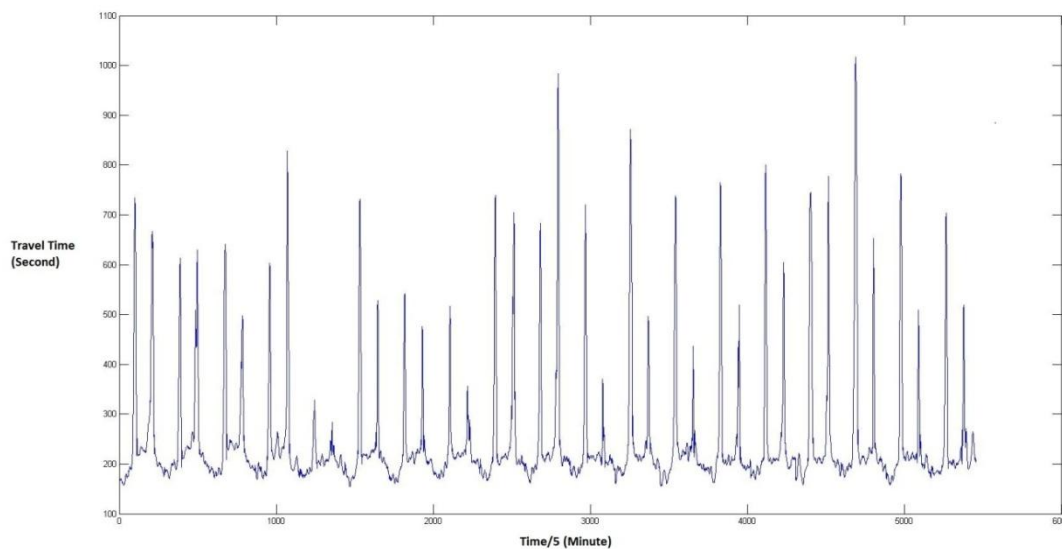
3.3. Fitting suitable SARIMA (p,d,q)x(P,D,Q)$_s$ model on data

As illustrated in Figure 6, travel time patterns have a recurrent trend with a seasonality of 24 hours. Although these recurrent profiles have different peaks after comparing the mean value from each day data, it is observed that the mean values fluctuate around a constant value and the daily mean value does not dramatically increase or decrease. Based on this observation the current historical travel time data base is recognised as a stationary time series and there was no need for differencing. For any other route experiencing an increase or decrease in the daily mean TT value, a first or second degree of differencing will be needed to turn the time series into a stationary one. But for the current historical data of the study routes, there is no need for differencing and the "d" indicator is defined as zero in the SARIMA model.

The next step is defining suitable values for indicators ("p","P","q" and "Q"). As explained before, these indicators define how much the previous continuous lags and seasonal lags contribute to forecasting the next lags. These indicators primarily are defined using ACF and PACF graphs. Basically, the "q" is defined as the point in the ACF graph where no more spike can be observed after that. Using the same method, the "Q" is defined from seasonal ACF graph. Repeating the same procedure with PACF graphs, the related values for "p" and "P" are obtained. Subsequently, the suggested model is calibrated on half of the historical data for forecasting each day travel time. Then the model is validated on the second half of data and final parameters selected. Based on the characteristic of data in the selected sample corridors, the indicators for "p & q" are chosen between 1 and 2 which means that,

the prediction mostly dependes on one or two lags before and one or two lags in previous seasons (same day from last weeks).

Predicting travel time of each day, historical databases consist of data from almost 18 to 25 days before the specific day. For example, predicting travel time in a sample day Monday, with a historical data base shown in Figure 6, 19 Mondays before that sample day are used as historical data. Half of this data (10 days) is used for calibration of the model and the second half (9 days) is used to validate the created model.

Simplification of the prediction process, the 24 hours of a day are divided to 5 minute groups which means that each day consists of 288 travel time data points. Therefore, by putting all similar days continuously together, the seasonality is defined as 288 in the model. Indeed, the number 288 refers to the data point in the previous 24 hours (in the previous season).

For predicting travel time values in a sample day, the "p,d,q" parameters are defined as "1,0,1" with one day seasonality (288). Then the "P,D,Q" are automatically generated by the model . The model is fitted on half of data and coefficients estimated by the model are shown in Table 1. Thereafter for the next half of data the sum of the squared residuals (SS_{res}) from the fitted model is calculated. The sum of the squared differences from the mean of the real values (SS_{tot}) is also defined. Finally the coefficient of determination "R^2"[2] is calculated as 0.794 for the model. This demonstrates that the fitted SARIMA model predicts 79% of the variance in the historical data.

Table 1: Sample model's coefficients and equation

Parameters	Estimated Coefficient
Constant	-0.017
'AR'	0.962
Seasonal 'AR'	-0.105
'MA'	0.668
Seasonal 'MA'	-0.593
Variance	50.114
$X_t = 0.96X_{t-1} - 0.1X_{t-288} + 0.66a_{t-1} - 0.59a_{t-288} - 0.017$	

3.4. Defining different prediction horizons for forecasting process

Prediction horizons are the number of lags (minutes) which will be predicted after real available travel time values. For predicting short term travel time in future, different horizon time is defined in this paper (5, 15, 30, 45, 60, 90 Minutes). For example in case of 15 minute prediction horizon, real data is available until 7:45 and the value for 15 minutes later which is 8:00 is predicted. Then for predicting 8:01, the real data till 7:46 is used and forecasted 15 minutes later. Therefore, through defining different prediction horizons, accuracy of short term prediction is tested in variety of time periods.

4. Results and discussion

Prediction results for several days in all three chosen study corridors are compared. This is performed within different time horizons to evaluate the prediction's accuracy for each time horizon separately.

Figure 7 is a schematic view of the comparison between real travel time series and predicted ones for a sample day in Coronation Drive. In the figure different colours are used to show various predicted travel time series within different time horizons. From this figure, it can be

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[2] R^2 = 1- (SS_{res} / SS_{tot}) indicates how closely values are obtained from fitting a model match the dependent variable the model is intended to predict.

clearly seen that the predicted time series change with alteration of time horizons. This figure also shows that changing the prediction horizon from 5 minutes to an hour causes an increase in error of prediction.

**Figure 7: Real travel time series and forecasted ones in different time horizons for a sample day**
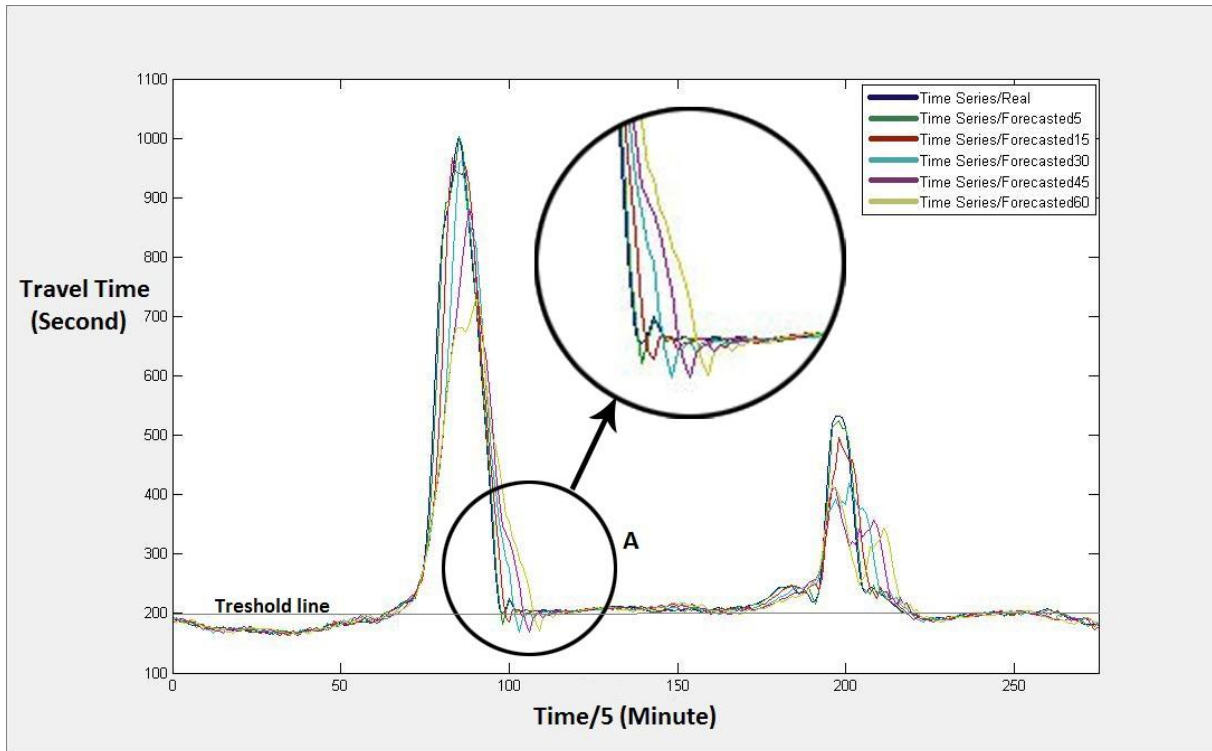
SARIMA prediction's results show a good accuracy in terms of having few amounts of lags between real travel time series and predicted one. This means that, there is not a considerable lag in congestion start times between real and forecasted trends. However, in most of the cases there is a drop in predicted trend after Congestion periods (peaks in time series). This drop is clearly shown in section "A" in Figure 7. By increasing the prediction horizon length, this drop in predicted travel time trend increases as well. The reason behind this issue is that when the prediction horizon increases, SARIMA uses previous lags which are predicted by the model, not the real data. For instance the model has predicted two lags after the real data points with associated error, then these values are used for predicting next lag .Therefore, error will dramatically increase, specifically when the difference of two continues lags are high (like in congestion build up and congestion dissipation parts).

To solve this problem in short term travel time prediction, a threshold quantity, based on the whole day travel time trend can be considered. In this case the threshold value is defined based on free flow traffic in non congested periods. For example, for the sample day in Figure 7, the threshold line is shown. The constant value for drawing this line is estimated based on free flow travel time mean calculation. Then predicted values (located just after the peaks) less than the threshold are replaced with the threshold value.

As the most challenging part of travel time prediction is predicting congestion periods (peaks in time series), the main investigations are carried out on the peak periods [morning (6:30-9:00 am) and afternoon (3:30-7:00 pm) congestions]. The graphs in Figure 8 also show the difference between real travel time values and predicted values due to use of different

prediction horizons in SARIMA Modelling. In each graph vertical axis represents the difference between real and forecasted travel time in seconds and the horizontal axis represents congestion time periods (shown in 5 minutes intervals). These graphs are classified from 5 to 90 minutes prediction horizons and show the comparison only on peak periods. In each part, the upper bar chart is related to morning peak (6:30-9:0: am) and the lower one provides information about afternoon peak (3:30-7:00 pm).

Figure 8: Difference between predicted and real TT value for the sample day (in different prediction horizons of 5, 15, 30, 45, 60 & 90 minutes)
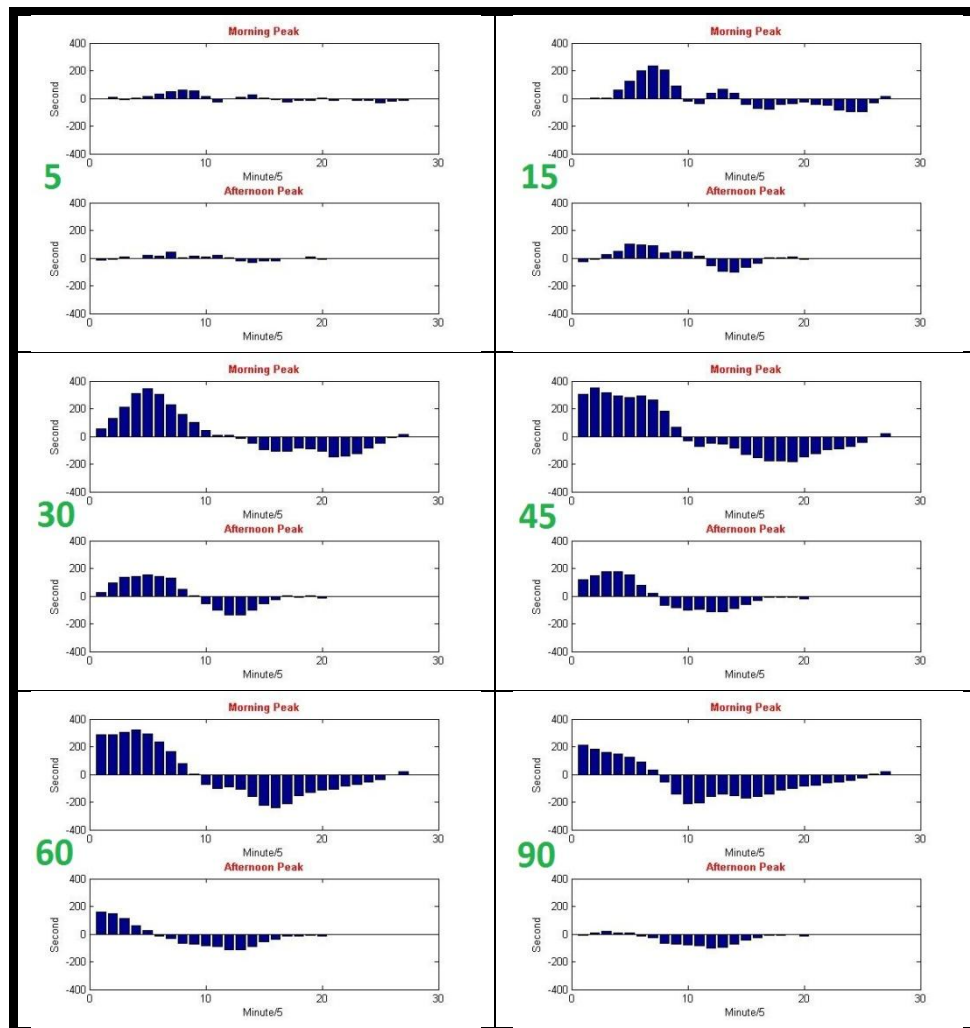

As shown in these graphs, increasing the prediction horizon results in increase of the difference between predicted and real travel time value. This error gets to its highest level at 45 minutes prediction and then falls down slightly and becomes constant after one hour.

To evaluate the selected model results within each prediction horizon, the percentage of error during congestion periods is calculated for each predicted day. Then percentages of error for all results are illustrated in the charts in Figure 9. These bar charts show the percentage of the error occurred within each prediction horizon only during peak periods. These values are calculated by MAPE (Median Absolute Percentage Error) method.

The following equation is used as MAPE equation for comparing real travel time values and the predicted ones. In this formula R_t represents the real travel time values and the F_t stands for the predicted ones.

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{Rt - Ft}{Rt} \right| * 100$$

Figure 9: SARIMA prediction errors in different prediction horizons (congestion periods)
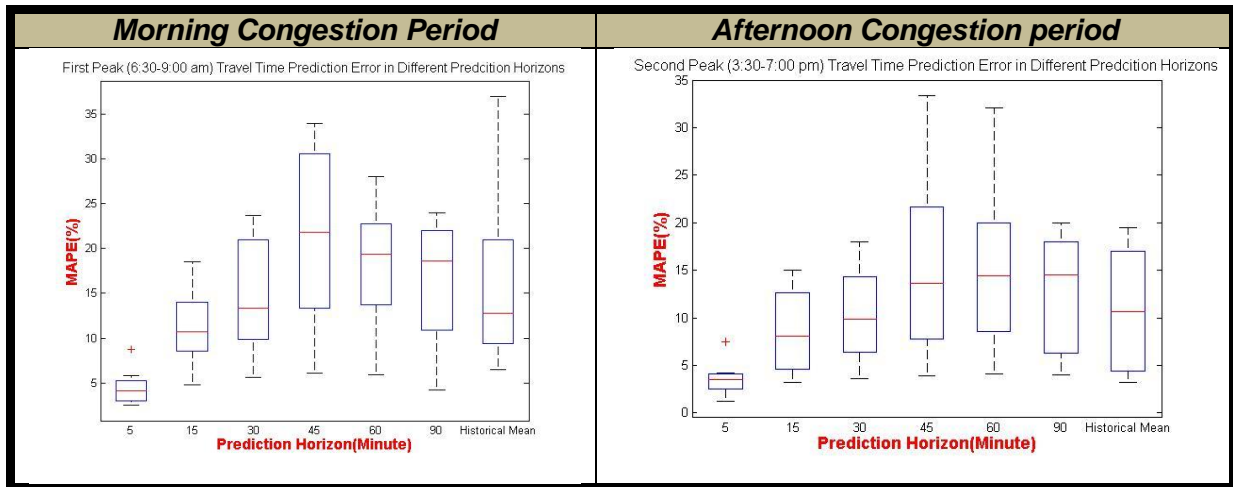
The calculated errors for predictions by SARIMA are shown for 5 to 90 minutes prediction horizons separately in Figure 9. The last vertical bar in the right side of each graph is related to the calculated error for predicted travel time values using historical mean method. The historical mean method is a simple naive method for forecasting an approximate future values in time series based on calculating the average values from historical data. According to this graph distribution of prediction error rate by SARIMA is acceptable as long as it is not above the historical mean error. From the charts it can be concluded that SARIMA prediction model works efficiently for predicting short term future up to 30 minutes.

Besides, the reliability of prediction by SARIMA is evaluated by using E_{90} indicator. E_{90} is the 90th percentile of absolute percentage error of predicted values.

Figure 10: 90th percentile of prediction error in different prediction horizons (congestion periods)
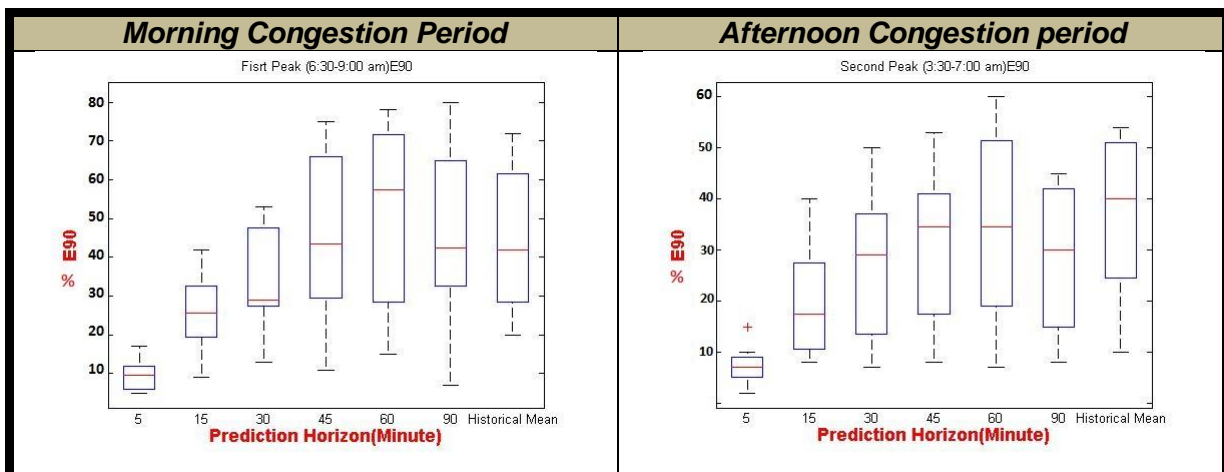
E_{90} value shows that 90% of predictions have less error than this value. Represented results in Figure 10 approve the previously results assessment for all three routes with different traffic conditions.

Based on the results taken for all three case study corridors, SARIMA model shows acceptable prediction results up to 30 minutes during peak hours. This statement is

concluded by assessing the results of explained MAPE method in Figure 9. Besides, the reliability of the method is evaluated by E_{90} indicator in Figure 10. This assessment also shows that the travel time prediction by SARIMA method in at least 90% of the cases have better results than historical mean with a considerable rate of difference in errors. Discussing the results focused on congestions, implies that this method works much better during other periods in daily travel time.

SARIMA performs better in predicting short term TT in signalised arterials when congestion occurs over a good shaped recurrent trend peaks. For example, Figure 11 shows two popular types of peaks in travel time series. In section "A" there is a sharp peak representing a dramatic increase and decrease in travel time during a short period of time but it does not show fluctuation. In contrast, the peak in section "B" is a sample of wide peak with congestion build up and congestion dissipation happening gradually over a longer period of time. But as it can be clearly seen , these type of peaks usually show more fluctuation. The type "B" peaks are basically created when there is a lack of data points for estimating the corridor travel time.

SARIMA model generally predicts type "A" peaks with less error compared to type "B". In the case of fluctuating wide peaks, travel time changes between two continuous lags do not follow a reasonable pattern. So the model cannot make a good relation among these data points for predicting the future lags. But for good shaped regular peaks with normal behaviour, SARIMA model performs better. Consequently, for the arterial routes which show good shaped peaks (like type A) in their travel time series, SARIMA attains better results compared to other traffic conditions.

Figure 11: Showing sharp peak & smooth peaks in a sample day travel time profile
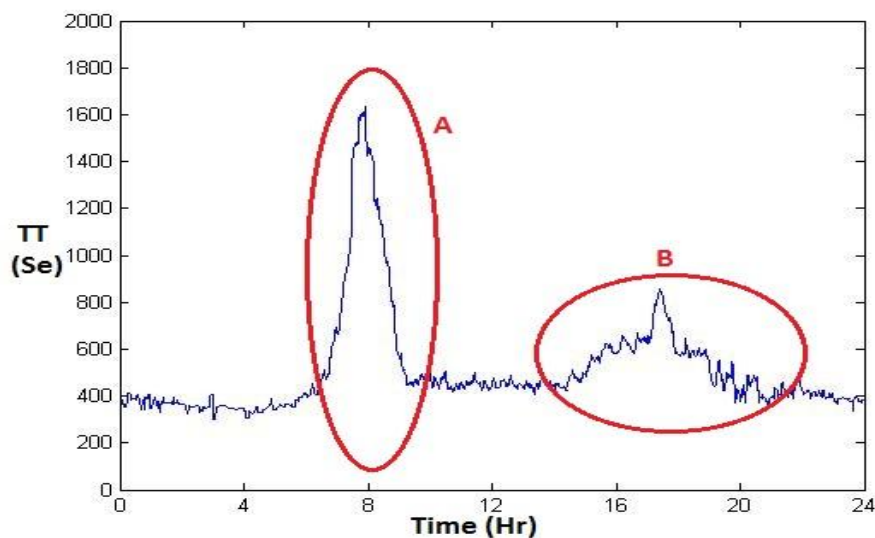
Generally the model's prediction error rate in longer prediction horizons increases by having intense congestion build up or congestion dissipation in daily travel time series in any corridor. There is also a variation in day to day congestion start and end times. So in this situation, model's accuracy for forecasting congestion travel time is decreased.

5. Conclusion

This research first developed a Bluetooth based travel time database for three different signalised arterial corridors. A SARIMA model was calibrated and fitted to each database with its prediction results evaluated for all predicted days separately, by comparing them with real travel time data. The focus of the analysis is on congested conditions. The drops after the peaks generated by SARIMA were then replaced with a minimum value by defining a threshold based on same day free flow traffic condition, as an attached part to the prediction process.

Accordingly, the SARIMA model produced good results for short term travel time prediction up to 30 minutes ahead. Predicting future values in longer prediction horizons, means prediction errors will increase due to the high variability in the day to day travel time trend.

Generally, the accuracy, robustness and transferability of the model with the calculated rate of error were all evaluated by testing it on three corridors with a variety of traffic conditions. These results focused on congested periods concluding that the model performs much better in arterial corridors with normal shaped congestion peaks. These peaks generally are created by sufficient data points rate and with more similar recurrent trends in their historical travel time databases.

Overall, the SARIMA modelling application in terms of short term travel time prediction on Bluetooth data can be further improved by increasing the quality of historical travel time estimates. To do so requires more reliable historical databases by applying better clustering methods. Increasing the confidence of corridor travel time estimation by improving the rates of travel time data points is also recommended. This can be achieved by fusing Bluetooth with loops.

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