

Global Navigation Satellite Systems (GNSS) Equipped Public Transport Buses as Information Sentinels

Oluropo OGUNDIPE, United Kingdom

Key words: Transport, GNSS, Data, Modelling, Bus

SUMMARY

The ability to predict, plan and prepare for the different usage patterns and traffic/road user load is very important to city transport planning, logistics & haulage industry, as well as emergency planning and other sectors. Increasingly around the world public transport buses are being equipped with GNSS receivers to help provide accurate timetable “countdown” information to awaiting passengers at bus stops or via mobile apps. This information if analysed at different levels of abstraction and correlated with other data sources such as road works, sporting events and other activities can provide useful insights which can enable forward planning and resource allocation. In this regard a short feasibility project was conducted in the UK as part of the IMPETUS University partnership between the University of Nottingham, Leicester and the Transport Systems Catapult. For the project, GNSS data from Transport for London (TfL) buses was collected and analysed. Utilising bus data produces an additional level of complexity due to stopping at bus stops along the route. However analysing the stopping pattern can also provide useful information on user demand and usage pattern. There are over 8500 buses in London serving over 700 routes. Therefore a vast amount of data is collected daily by TfL’s iBus system.

For this study the area of interest was narrowed down to ten routes passing in and around the Wembley area. Two weeks data from before and during the FA football cup final was collected. Geo-tagged door event data was collected along with the number of satellites for that epoch. Also GNSS position data every 5secs was extracted from the database along with the velocity. Complementary data on roadworks in the area was also collected. Data parsing and cleaning first had to be performed before any further analysis could be conducted. The bus data collected was ‘dirty’ – fragmented data, gross errors, multiple repeated data, in particular with the door event data. After cleaning, the number of door events was aggregated into 2hour and 30mins bins respectively, plotting this over time for each route showed clearly the daily usage trend such as the rush hour periods. The pattern of the “normal weekend” vs “FA cup weekend” was compared. Distinctive change in pattern between the data sets could be observed. Independent Component Analysis (ICA) was tested for extracting common features from the routes, this gave mixed results. Empirical modelling of the data for each route by curve fitting to a 5th degree polynomial was also tested. The velocity and headway (distance between buses) was also analysed. The data on the number of satellites in view was used to create a map of the satellite visibility corridor. Bus route data is complex and difficult to analyse as it is affected by a myriad of factors. Attempting to isolate cause and effect is difficult, however the GPS data provided useful insights to enable prediction which can aid planning for adequate service provision.

Global Navigation Satellite Systems (GNSS) Equipped Public Transport Buses as Information Sentinels (8209)
Oluropo Ogundipe (United Kingdom)

FIG Working Week 2016
Recovery from Disaster
Christchurch, New Zealand, May 2–6, 2016

Global Navigation Satellite Systems (GNSS) Equipped Public Transport Buses as Information Sentinels

Oluropo OGUNDIPE, United Kingdom

1. INTRODUCTION

Intelligent mobility is an increasing sector of the transport industry and data (access, handing, analysis, dissemination), is at the heart of it. Intelligent Mobility is defined as the “*smarter, greener and more efficient movement of people and goods around the world*” (TSC, 2015). The increasing availability of connected sensors (internet of things) at lower costs is enabling system observation and data collection like never before. Global Navigation Satellite Systems (GNSS) have enabled positioning of the user anytime and in any geographic region. GNSS constellations are increasing with the well-known US NAVSTAR GPS being joined by other systems such as the Russian GLONASS, Chinese Beidou and Europe’s Galileo. GNSS receivers are increasingly ubiquitous and can be found on mobile phones, vehicles, wristwatches and a range of other devices. This increase in the number of sensors has led to a significant increase in the volume and types of data related to mobility. However data in itself does not add value but rather its exploitation to add service improvements and optimisation, as well as its ability to provide an ‘on-demand’ service relevant to real-time user needs. In times of emergency or disaster, the ability to adapt a transport system in real-time to meet the urgent needs of the users would be invaluable.

Providing the public transport needs for a large city such as London with over 8.5 million residents not including tourist and other visitors is not a trivial task. This responsibility falls on Transport for London (TfL) who oversee the underground train network (Tube), certain over-ground rail lines and the London Bus network. There is the need to provide a regular bus service on over 700 routes with 8500+ buses. These routes are run by a range of operators. TfL needs to manage the system, ensuring that the operators are providing the service according to the defined time schedules. In addition TfL needs to provide passengers with real time information to enable journey planning. This ‘countdown’ information is provided at the bus stops or via mobile apps. TfL itself does not develop the mobile apps but rather it makes the data available for free to developers via its Open Data API. This countdown data is derived from processing the real-time GPS data collected from the receiver units fitted on all its buses.

Global Navigation Satellite Systems (GNSS) such as the US GPS system enables the position of an equipped bus to be determination in real time. With the appropriate radio telemetry installed this information can be passed on to a central server for further processing. GPS position determination requires line of sight between the receiver and at least four satellites. In a city like London with its tall buildings and narrow roads, this is not always possible. As a result the TfL buses have an on-board unit (OBU) which utilises an integrated GPS + Inertial sensors system for position determination. The position accuracy is in the order of a few metres though outliers and reduced accuracy occasionally occur hence the need for pre-processing.

Global Navigation Satellite Systems (GNSS) Equipped Public Transport Buses as Information Sentinels (8209)
Oluropo Ogundipe (United Kingdom)

FIG Working Week 2016
Recovery from Disaster
Christchurch, New Zealand, May 2–6, 2016

The TfL buses navigate the roads and streets of London and as a result are affected by the prevailing conditions such as roads works, obstructions such as vehicle breakdowns, and traffic congestion due to sporting events or rush hour activities. Thus the GNSS equipped buses can act as ‘sentinels’ in the transport system and analysis of the geospatial data has the possibility to provide information to aid traffic planning and resource deployment. However this is quite a complex task as the effects of the various driving forces on the data combine in complex ways or are masked due to other factors, e.g. in some areas there are specialised bus only lanes at given times.

There are infrastructure based sensors such as induction loops, at specific locations under certain roads and motorways. Inductive loops installation and maintenance is difficult and disrupts traffic. Thus its coverage is sparse. Analysis of the GPS data does not require additional infrastructure as this data is already collected.

2. DATA COLLECTION

Collecting data from over 8,500 buses requires an infrastructure and telemetry architecture to enable the observation, storage, processing and dissemination of the data.

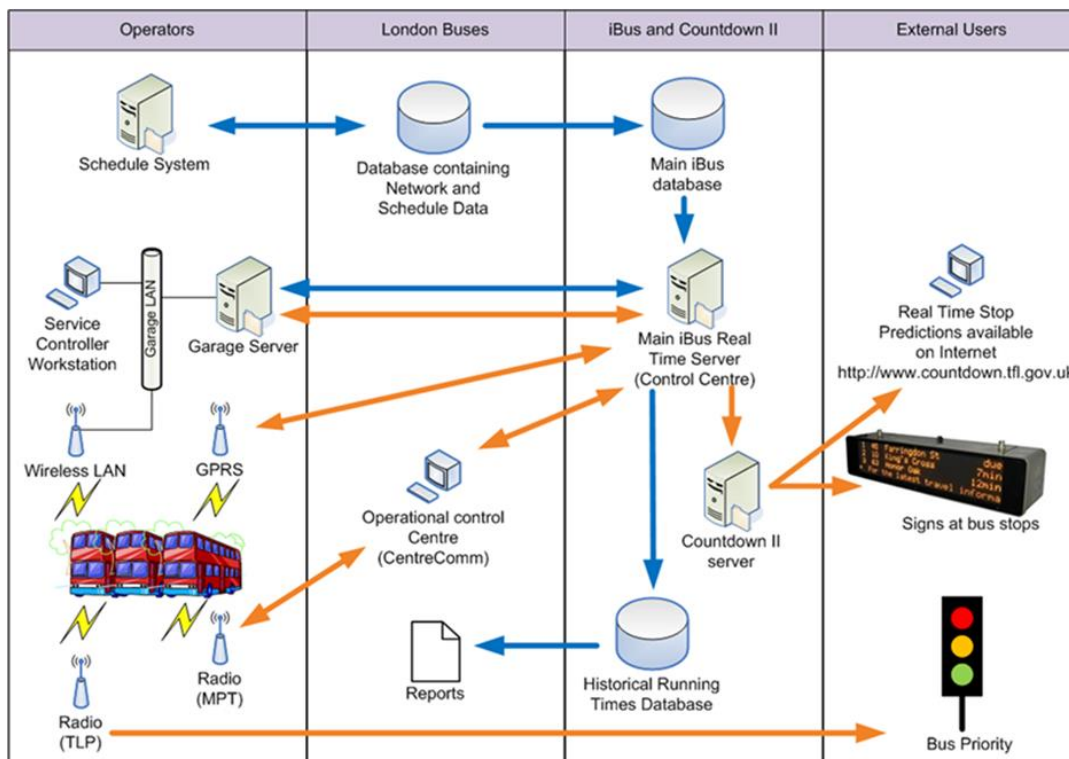


Figure 1: TfL iBus System

The TfL system to enable this is referred to as the iBus System as shown in Figure 1. A vast amount of data is collected daily by the system, this includes vehicle ID, GPS position at 1Hz, position quality, number of satellites, door event, speed and numerous other data from the vehicle sensors. The door event data is comprised of the timestamp, position coordinates, heading and event tag when the bus door is opened or closed. Historical data is stored in the system database for 60 days. For this feasibility study the area was narrowed down to the Wembley area of London, collecting data from 10 routes passing in and around the area. Data was collected for the one week period two weeks before the FA cup football final, and also for the 1 week period of the FA cup final (which is a major football event taking place at Wembley stadium). GPS data including WGS84 latitude and longitude, velocity, position quality indicator and number of satellites every 5 seconds was collected from the database. This data rate is at a resolution to enable data analysis while reducing the data load. The door event data as well as, complementary data on road works in the area was also collected. This is available in XML format from the TfL Open Data site. Bus Stop coordinates in csv format is also available from this site. Visual representation of roadworks location and type is available from <https://roadworks.org>. By focusing on the Wembley area this enabled data to be collected around relatively 'normal' period of traffic and public transport usage versus a period of expected high traffic and usage around a major sporting event. Thus enabling analysis and comparison. Grid Inquest was used to convert from WGS84 to British Ordnance Survey Grid (OSGB_NG) coordinates.

The study methodology included the following steps:

- Data parsing
 - Reading the bus data in various formats.
 - Roadworks data in XML format
- Data cleaning
 - Anomaly detection
 - Data interpolation
 - Data smoothing
- Data analysis
 - Statistical analysis
 - Empirical analysis
- Data visualisation

An SQL query was run by TfL staff to extract the relevant dataset required.

3. DATA PRE-PROCESSING

3.1 Data Cleaning (Anomaly Detection), Data Interpolation, Data Smoothing

The data collected was noisy and fragmented and had to be cleaned before analysis. In general sensor data collection can be challenging on multiple levels. The sensor data often contains errors or incompleteness due to issues ranging from data bandwidth, lack of internal processing capacity or power problems. If these errors remain in the data it can lead to uncertainty or false outputs in the data analysis and representation (Aggarwal, 2013). Large volumes of data such as the bus data

collected also pose a challenge in terms of data storage and processing. Some of the issues faced included:

- There were gross errors which needed to be removed.
- Door event data which contained multiple repetitions that needed to be removed.
- Data interpolation required to fill in data gaps.
- Data smoothing was done using a moving average filter, with the option of using a Kalman Filter.
- All of this needed to be done while avoiding removing correct data or leaving significant amount of wrong data which may lead to erroneous results.

4. DATA ANALYSIS – INFORMATION EXTRACTION

Following the data pre-processing the Door Event data was analysed. The Door Event data recorded the WGS 84 latitude and longitude of the bus position each time the bus door was opened or closed. A tag of '1' is recorded when the door is open and '2' when the door is closed. As mentioned earlier, this sensor provided a lot of challenges as it contained errors, fragmentation and repetitions. In addition other fields such as vehicle speed, quality indicator and number of satellites in view were also recorded.

4.1 Data Aggregation – Door Event Data

The Door Event data was aggregated into 2 hourly bins over the course of a day. The basis of this was that the door event data serves as a proxy for user load or demand. Thus analysis of this data can provide an indication of the user load or demand pattern with time. Figure 2 shows a column graph of the Door Event data for 4 routes in the Wembley area on Friday the 15th 2015.

Friday 15th

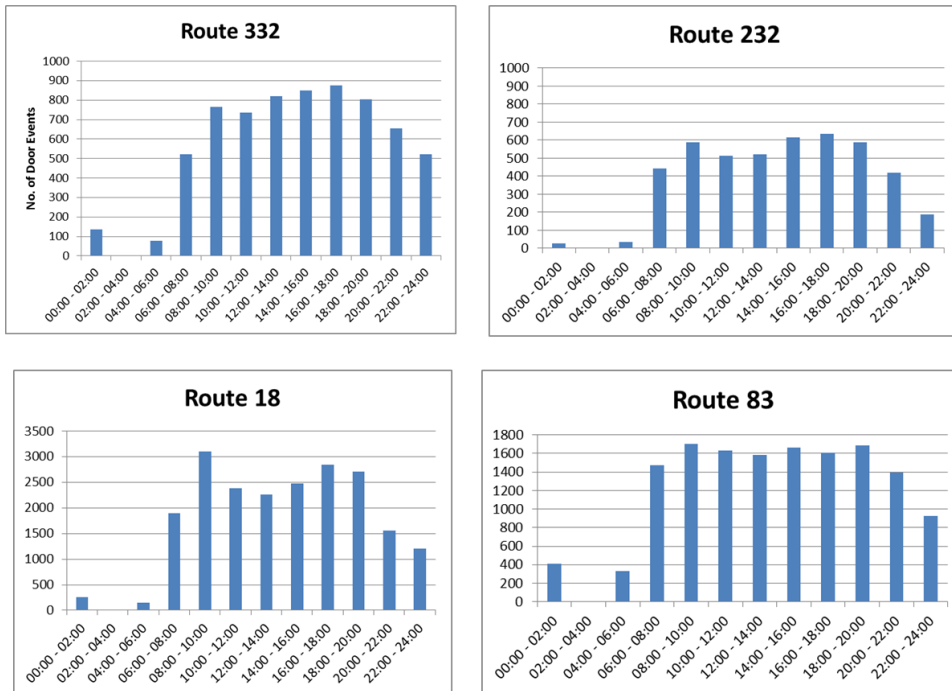


Figure 2: Aggregated Door Event Data (2 Hour Bins)

From the graphs in Figure 2 the morning rush hour peaks between 8 – 10am and the evening rush hour between 16:00 – 20:00 can be seen. Also the London Bus service starts at about 5 am with buses gradually coming into service and closes at about 1:30 am with buses gradually going out of service and returning back to the bus depot. This pattern can also be seen clearly in the graphs. While each route exhibits its own trend, these general patterns can be seen in the data. Factors such as number of schools, large organisations, and other attractions like museums and theatres along a particular route would influence the usage pattern and thus door event data for that route.

The total number of buses serving a particular route on a day differs per route. Therefore in attempting to compare routes based on user demand the Number of Door events was divided by the total number of buses on the route. This is shown in Figure 3 for seven of the 10 routes selected.

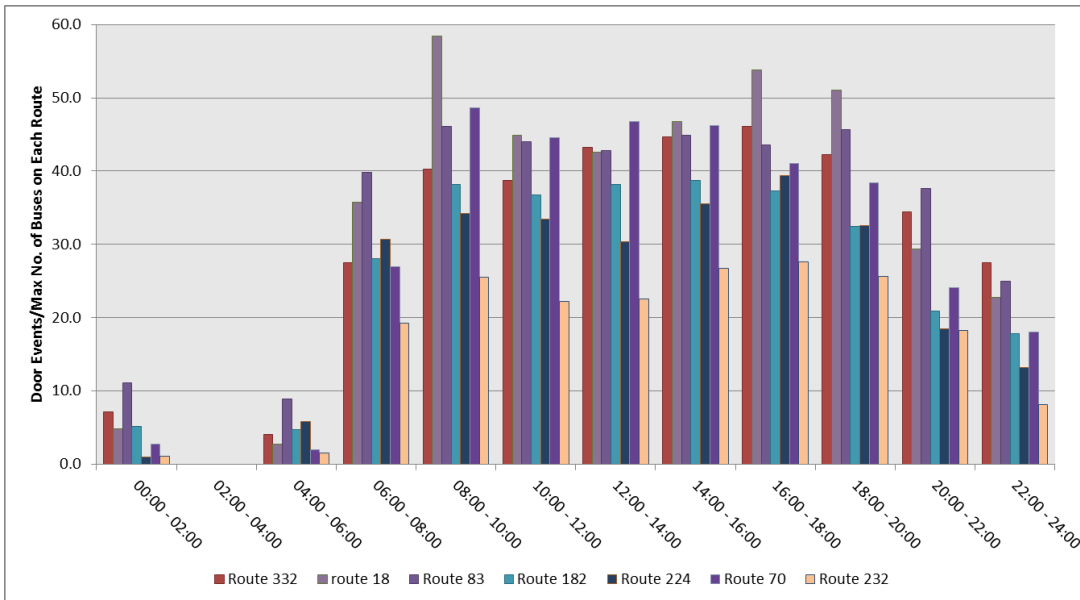


Figure 3: Normalised Door Event ‘Histograms’

From Figure 3 it can be seen that Route 18, Route 83 and 70 comparatively have the greater usage particularly during peak periods. Figure 4 shows that Route 18 goes through central London passing by major train stations, offices and tourist attractions as well as on the west side passing close to the Wembley stadium.

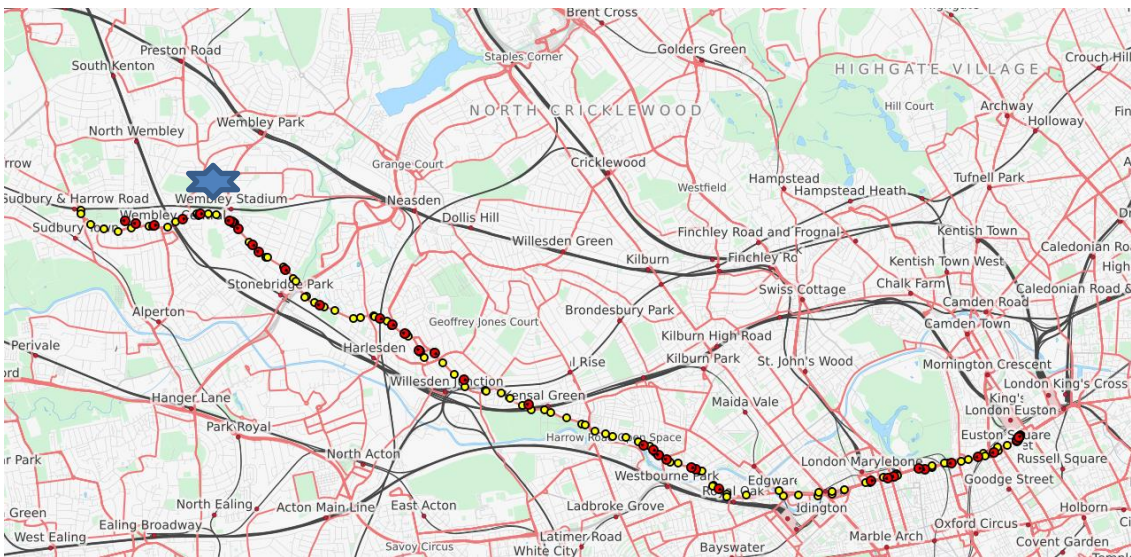


Figure 4: Path of Route 18 (www.traintimes.org.uk)

Further analysis was done in order to assess whether the impact of a major sporting event at the Wembley stadium could be picked up by analysing the door event data. The aggregated door event data for a ‘normal’ weekend (Friday and Saturday) was compared with that of the ‘FA Cup Final Weekend’.

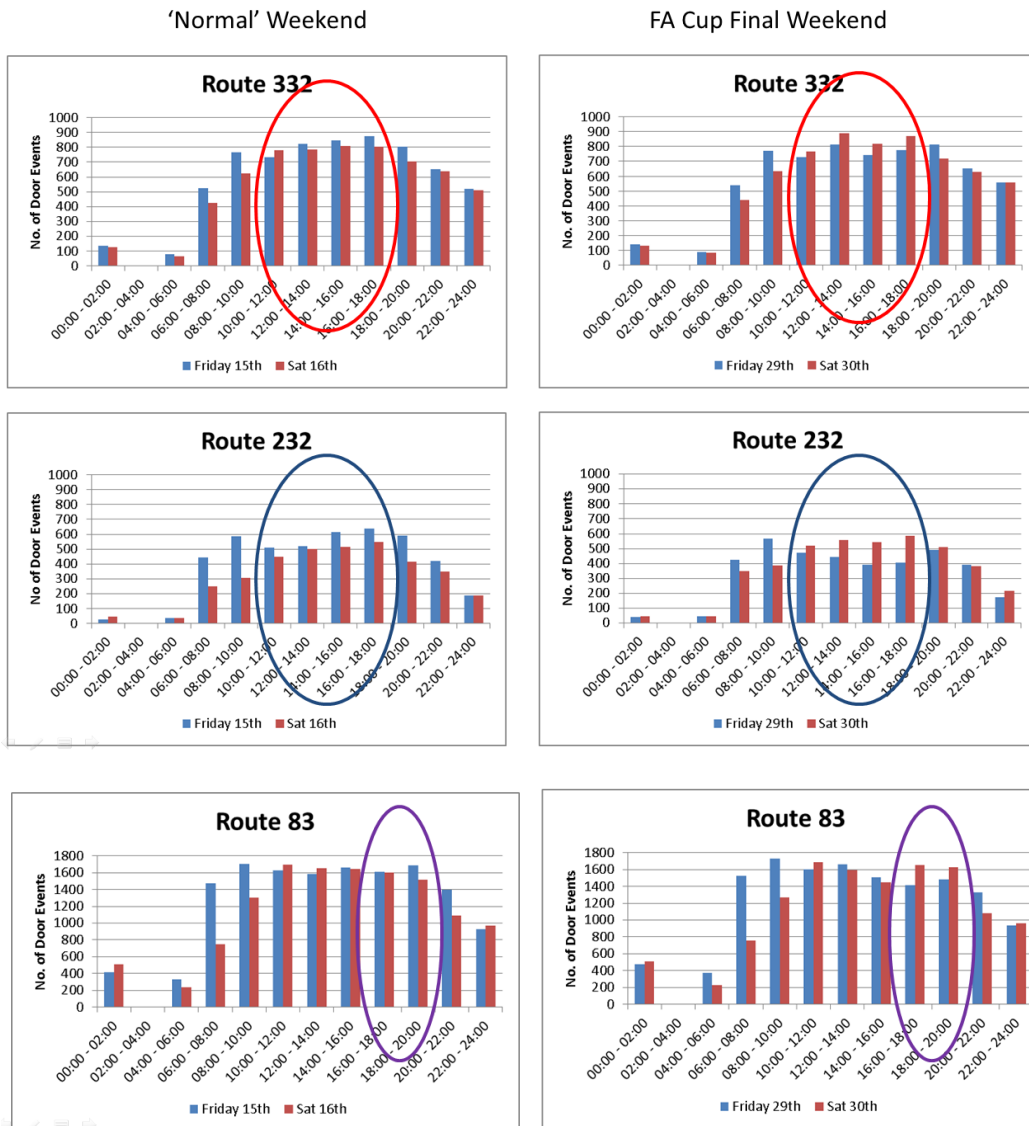


Figure 5: Comparison of Door Event Data – ‘Normal’ Weekend vs FA Cup Final Weekend

Routes 332 and 232 show distinctive change in pattern from the ‘Normal’ weekend during the time period of 12:00 – 18:00. Where for the normal weekend during that period the door events on the Friday are greater than that on Saturday, on the FA cup day (Saturday 30th) the number of door events exceed that of the Friday (29th). The Wembley Stadium gates open at 15:30 on Sat 30th for the FA cup match, with the match starting at 17:30. Route 83 also shows a change in pattern however this is in the period of 16:00 – 20:00. This may capture both the pre-match arrival and post-match exit activity. Other routes such as Route 18 which pass through the area do not show any distinctive change in pattern that could be identified in the aggregated data. It may be that

aggregating the data in 2 hour bins or analysing the data at a route level has masked the effect on the data for such a busy route as Route 18.

4.2 Modelling Using Independent Component Analysis

Independent Component Analysis (Hyvärinen and Oja, 2000) is a form of blind source separation which is utilised for signal separation and feature extraction. It is used to separate source signals from their mixtures. ICA has been applied to EEG data to reveal information on brain activity. It has also been applied to high rate (20Hz) high precision GPS data used for structural deformation on a suspension bridge to separate between the bridge deformations and multipath noise using a joint empirical mode decomposition (EMD-ICA) technique. (Dai et al., 2014). Depending on the input data, the independent components can indicate some physical characteristic, thus ICA can be seen as a data mining tool. It was used by Dai et al. (2014b) to extract the independent components of monitoring data from wire alignment sensors on the Wuqiangxi Dam in China, these were directly correlated with causative factors such as temperature and water level. The TfL bus data was analysed using ICA. The aim was to assess whether by using this technique common key causative factors can be extracted from the door event data of the different routes. This can then be used to model for future events to enable adequate provision of service – “Predict and Provide”.

If we observe n linear mixtures x_1, x_2, \dots, x_n of n independent components:

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \dots + a_{jn}s_n \text{ for all } j \quad (1)$$

This can be written as:

$$x = \mathbf{A}s \quad (2)$$

Where x is the random vector whose elements are the mixtures x_1, x_2, \dots, x_n , s is the random vector with elements s_1, \dots, s_n and \mathbf{A} is the matrix with elements a_{ij} .

Equation 2 describes the ICA model. The independent components cannot be directly observed. The mixing matrix \mathbf{A} is also not known but will be estimated based on the observed random vector x . There is an assumption of statistical independence (and that the mixing matrix is square). Therefore we can obtain the independent components as:

$$s = \mathbf{W}x$$

Where \mathbf{W} is the inverse of \mathbf{A} .

ICA aims to obtain the separation matrix \mathbf{W} based on optimisation and learning rules without prior information about matrix \mathbf{A} or the source signals.

4.2.1 Pre-Processing for ICA

Some pre-processing techniques are used to improve the performance of the ICA estimation. These include centring and whitening.

Centring: It is necessary to subtract the mean vector $m = E\{x\}$ so as to make x a zero-mean variable. This implies that s is also zero mean.

After obtaining the estimates of s , the mean can be added back.

Whitening:

After centring the observed vector x is then transformed linearly to produce a vector \tilde{x} whose components are uncorrelated with variances equal to unity.

$$E\{\tilde{x}\tilde{x}^T\} = I \quad (3)$$

Eigenvalue decomposition is a popular method for whitening and it also enables dimension reduction to be done in parallel. This helps to reduce noise and complexity.

The ICA model has two key ambiguities:

1. It is unable to determine the variances of the independent components (ICs). Thus it is assumed that each has unit variance. There is also the ambiguity of the sign where an IC could be multiplied by -1 without there being an effect on the model.
2. It is unable to determine the order of the independent components.

4.2.2 Fast ICA

The FastICA is a fast, optimised and iterative algorithm for computing the ICA which is based on an approximate computation of negentropy. Negentropy is a measure of non-gaussianity of a variable. The more non-gaussian a variable is, the greater the negentropy. Negentropy is computationally difficult hence an approximation is used in the Fast ICA.

Negentropy J:

$$J(y) = H(y_{\text{gauss}}) - H(y) \quad (4)$$

Where $H(y)$ is the entropy of y .

The general steps (following centring and whitening) are:

1. Choose an initial (e.g. random) weight vector \mathbf{w}
2. Let $\mathbf{w}(k+1) = E\{\mathbf{x}g(\mathbf{w}^T(k)\mathbf{x})\} - E\{g'(\mathbf{w}^T(k)\mathbf{x})\}\mathbf{w}$ (5)
Where g is the derivative of a non-quadratic function.
3. Let $\mathbf{w}(k+1) = \mathbf{w}(k+1) / \|\mathbf{w}(k+1)\|$ (6)
4. If not converged, go back to step 2

Details can be found in (Hyvärinen and Oja, 2000). The Matlab source code for the FastICA is available from: <http://research.ics.aalto.fi/ica/fastica/>

The 2 hour aggregated door event data for 7 of the 10 selected routes was used as input with each route regarded as an input signal. The data was normalised by dividing by the total number of buses on each route for that day. Figure 6 shows the input signals.

The data was processed using the FastICA. Based on the output of the EVD dimension reduction to 6 signals was done. The FastICA was configured to output 4 IC's. This was a user selection based on some intuition of the number of driving factors that may be contributing to the output signal. Figure 7 shows the 4 output ICs for Friday the 15th. While it is difficult to ascribe each IC derived to an external characteristic, the peak trends and rush hour peaks can be seen.

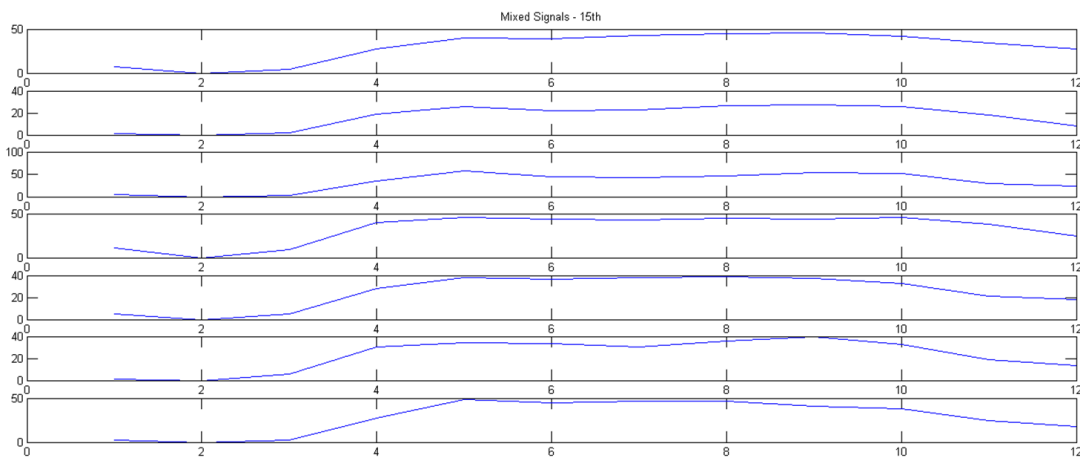


Figure 6: Normalised Aggregated Door Event Data from Friday 15th ('Normal Weekend') Used as ICA Input Signals

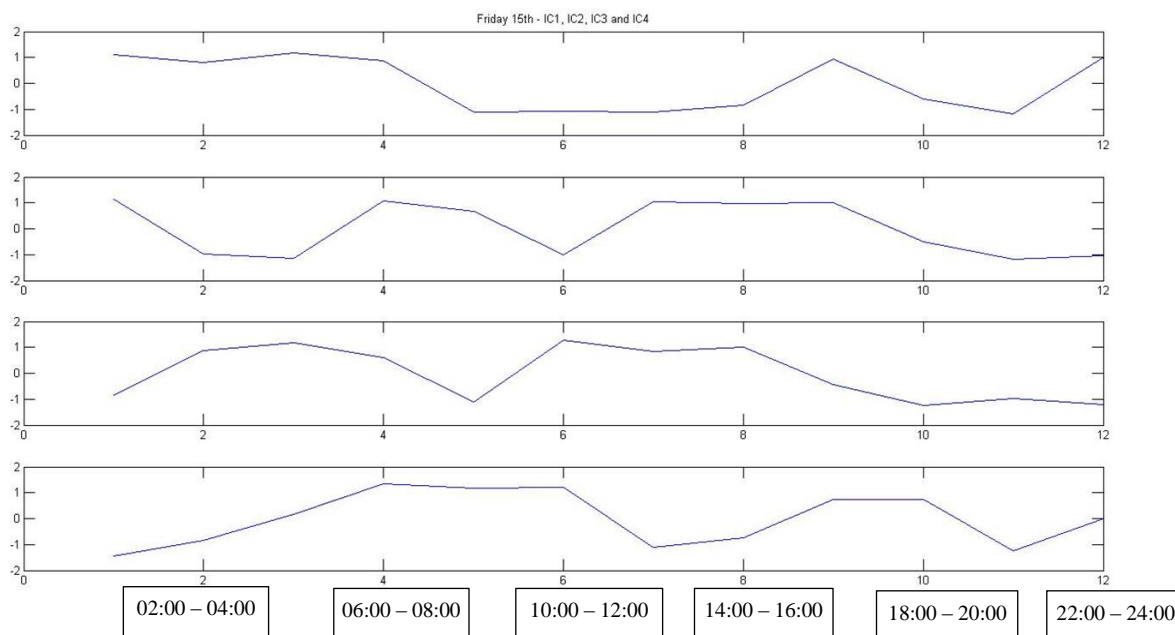


Figure 7: Independent Components from Friday 15th Door Event Data

Processing the door event data from the day for the FA cup final – Sat 30th gave the following results shown in Figure 8.

The aim is to try to find fundamental influencing factors common to all the 7 input routes. The four output ICs show varying patterns which correspond to different influencing factors. As mentioned earlier one of the key ambiguities of the ICA is that it is unable to determine the order of the independent components. To determine the interpretation of the ICs is the next hurdle. This requires other external data sources such as in Dai et al. (2014) where temperature and water level data was also available. This can then be validated using cross correlation.

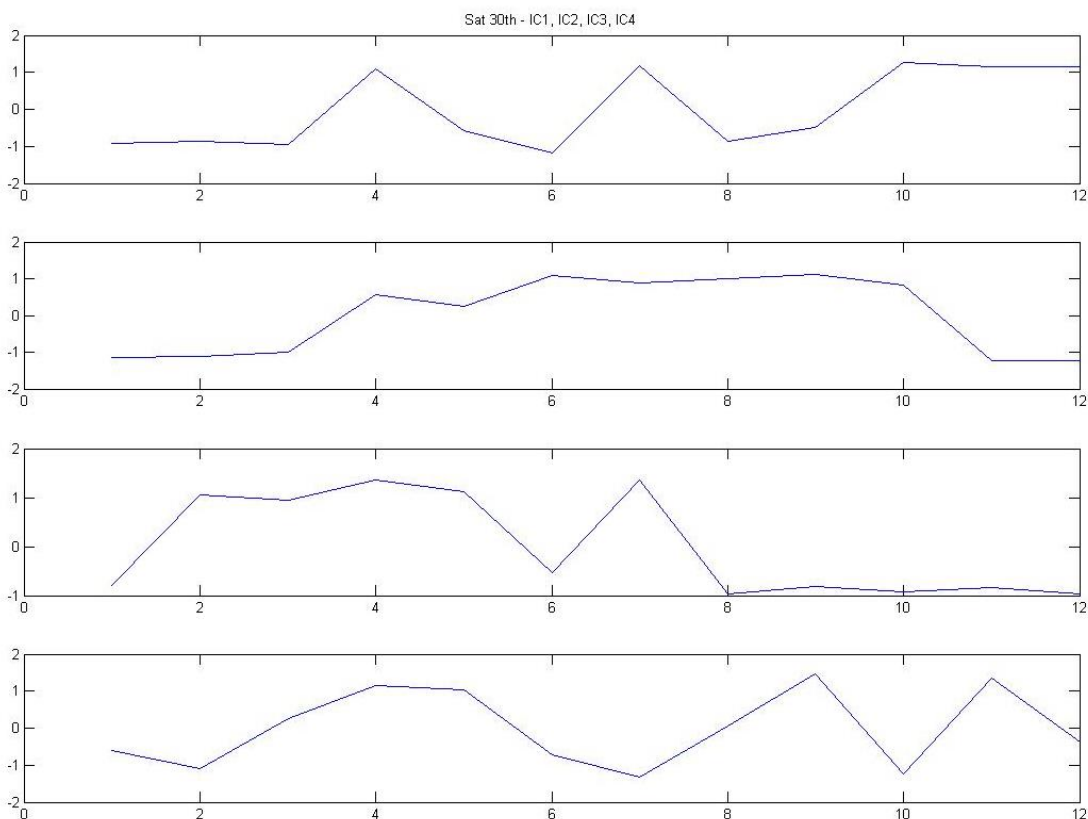


Figure 8: Independent Component (IC) Outputs of Sat 30th – FA Cup Day

The author's interpretation for the IC's are as follows:

IC1: Peak at Epoch 4 & 7 = 6 – 8am & 12:00-1400 respectively. This may be the effect of early morning workers and then mid-day shopping, as well as some effects of people going to the football match.

IC2: General trend - Day time vs Night time effects.

IC3: General morning activity then peak for the football start.

IC4: Peak at epoch 9 = 16:00 – 18:00 – may represent last minute arrivals for FA; peak at epoch 11= 20:00 – 22:00 – this may capture the fans departure.

The Door event data for Friday the 29th and Saturday the 30th was also tested using 30 minutes aggregated bins and z-score normalisation. The 4 output ICs for Friday the 29th showed clear trends and patterns however for the 30th the Fast ICA was unable to provide a solution for 4 output ICs instead 5 output ICs had to be generated. It was difficult to ascribe interpretations to the output ICs however it was felt that one IC was a function of the number of buses on the route, and another captured the peak usage times. It may be that Saturday has multiple localised factors influencing the bus user pattern hence common trends were more difficult to identify in the ‘higher resolution’ 30 min aggregated data.

Correlation with other external data sources such as number of fans exiting Wembley Train station, special changes in traffic rules, camera data, etc, would help to correlate and validate the output ICs.

4.3 Empirical Curve Fitting

An alternative method of modelling the data was tested. This involved fitting a curve to the 30 minutes aggregated door data for each route. This was done for the z-score normalised and centred data set which was used as the input for the ICA. The data for each route was modelled as a 5th degree polynomial. Based on this, and using the mean and standard deviation for each route, this can be used to predict future usage patterns. However this may be limited as it is only able to capture the general usage trends. Figure 9 show the curve fitting for Route 332.

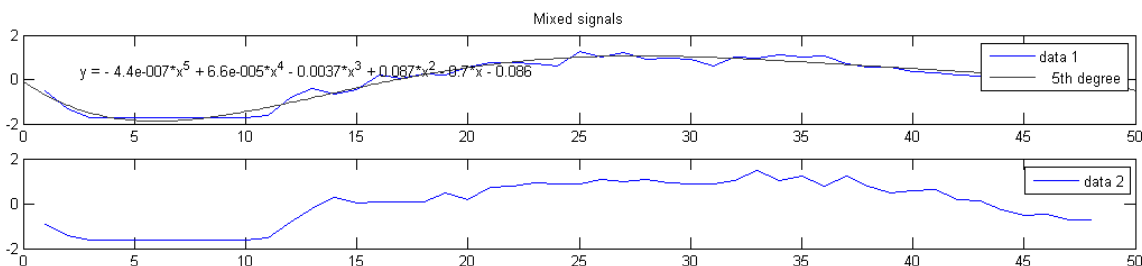


Figure 9: Curve fitting for Route Data

4.4 Vehicle Speed

The data collected also included the speed at which each bus was travelling. The vehicle speed would be influenced by a range of factors which include: the speed limit of the road, presence of traffic lights and pedestrian crossings, road traffic congestion, stopping to drop off and pick up passengers, usage of bus only lanes and more. The vehicle speed for any bus on the selected routes within a 10km radius of Wembley Stadium was aggregated into 30 minutes bins for each route. This is shown in Figure 10a for Routes 332. Selected sub-zones were created with 2km radius

around certain bus stops. Figure 10b shows the 5 mins aggregated speed for two specific buses on that route as they pass through these zones labelled ‘Box1’, ‘Box2’ and ‘Box3’. This enables the change in speed for the same bus in the same locations to be analysed for location specific as well as diurnal trends.

It can be seen that during the night time periods the vehicle speeds are high in the order of 30mph which is the general limit for residential areas. This would suggest a low usage of the buses on that route in that period and that the roads are clear of congestion. The period where there is no bus service (~02:00 – 05:00) can be clearly seen in Figure 10a and then the very early morning between 05:00 – 06:00 also have a relatively high average speed of about 25mph. After this there is a significant dip which represents the busy period.

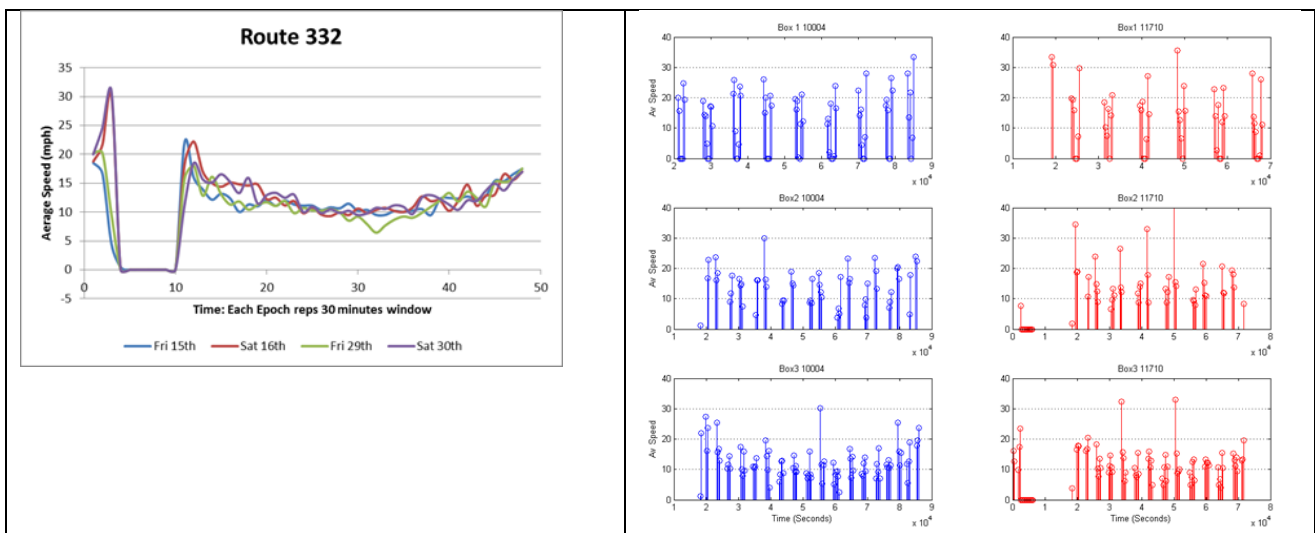


Figure 10: Aggregated Average Speed Data for (a) the Whole Route (b) Two specific Buses on Route 332 on Fri 15th

4.5 Satellite Visibility Window

Additional information that was included in the data collected was the number of satellites in view. This was provided along with the Door Event data therefore from the bus Door Event data a map was produced to show the areas of limited GPS visibility along the roads that make up the different routes. This information is important to many applications that utilise GNSS such as in-car navigation, logistics and the current development focus on autonomous cars. Knowledge of locations with poor GNSS visibility will enable the systems to utilise additional positioning resources or sensors at the appropriate times.



Figure 11: Satellite Visibility [©Google 2016]

The bus data was converted to KML and shown in Google Earth with the red dots indicating poor satellite visibility (0 – 3 satellites) and the green indicating good visibility (8 and above).

5. CONCLUSION

This paper has examined the use public transport buses in the city of London as information sentinels. As each bus traverses through the city it is affected by a range of factors which influence its movements and characteristics. This data if analyzed can be used for modelling passenger behavior or traffic dynamics in order to plan and prepare for high user scenarios. It can also enable proactive action and deployment of resources. Such planning and adapting capability is also relevant in a time of emergency or disaster as the ability to dynamically deploy buses to locations where they are most needed or to avoid hazardous locations will be of vital importance.

Tests were conducted using the Geo-tagged door event data as well as the detailed GPS 5Hz data from the buses of the 10 selected routes in the Wembley area. Other analysis was performed such as computing the headway which is the distance between each bus and also the door event duration. In addition further bus velocity analysis on the individual bus level was done. There was the issue of analyzing such a large data set during a very short feasibility study. Testing the ICA method with a different form of input data set may provide more definitive results as well as correlating with external data sources. The tests showed that the GPS bus data is complex and difficult to analyze. Significant pre-processing is also required. The buses are affected by a myriad of factors therefore attempting to isolate cause and effect is difficult. Though this feasibility study has shown that the data can give insights to enable prediction for adequate provision

Using the GPS data from the buses utilises existing data without the need for additional infrastructure to be set up e.g. induction loops. According to the Policy Institute for Wales, Open Data, open sourced software and crowd sourced data along with cloud computing capabilities are proving the resource and context for significant impact in analytical transport planning and offer the potential for reduced costs (Preston, 2014). Data analytics is a key requirement for proper transport planning and infrastructure management. The aim of modelling, such as those undertaken in this study, is to enhance understanding – e.g. of traffic patterns or user behavior.

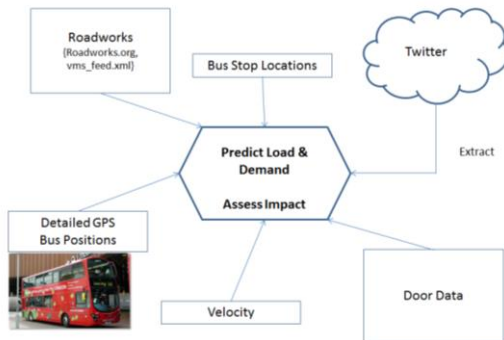


Figure 12: Possible Data Input Sources into a Predictive Analysis Platform

Pattern analysis of this nature, drawing on other available data feeds is widely expected to inform predictive analyses and autonomous system controls that will underpin intelligent mobility. Figure 12 shows a possible model of data input sources from the TfL buses and other external data sources for traffic and public transport usage modelling & prediction. Weather data would also be a valuable input. There are seven key aspects of the urban transportation problem (Preston, 2014): (1) Traffic Movement, (2) Accidents, (3) Peak hour crowding on buses and trains (4) Off-peak inadequacy of buses and trains (5) Difficulties for pedestrians (6) Environmental impact and (7) Parking difficulties. Modelling and predictive analytics based on the above model can provide insights into each of these key aspects. TfL already perform real-time monitoring of the fleet of almost 9000 buses and use the data for performance monitoring of their operators.

Understanding the operational service requirements of public transport such as optimal times, wait times, etc., will enable the provision of a service that caters to the user’s needs and thus increases their confidence and hence usage of the service. Buses can also be used as Vehicle Ad-hoc Network VANET sensors – providing other road users with information related to traffic conditions. This links with smart cities initiatives that are being established in many cities around the world. Intelligent Mobility has a wider impact that cuts across multiple industry sectors including commercial, social economic and environmental impact (TSC, 2015b).

This study investigated the use of geospatial related data for modelling however in a wider context modelling includes working with real time data, simulating environments, modelling human behavior and interactions, and more. A range of visualization tools are also required in order to develop the best ways of conveying the key information from the spatio-temporal data.

ACKNOWLEDGEMENT

This study was undertaken as part of the IMPETUS University Partnership Program between the University of Nottingham and Transport Systems Catapult. I would like to thank Mauro Manela and Simon Reed of Transport for London (Technical Services Group, London Buses) for their help and assistance in providing access to the data used in this study.

REFERENCES

- Aggarwal, C.C (ed.) (2013) *Managing and Mining Sensor Data*, NY: Springer, pp.1 – 7.
- Dai, W., Huang, D., and Cai, C., (2014) *Multipath Mitigation via Component Analysis Methods for GPS Dynamic Deformation Monitoring*. *GPS Solut* (2014) 18:417 – 428. DOI 10.1007/s10291-013-0341-9.
- Dai, W., Liu, B., Meng, X. and Huang, D., (2014b) *Spatio-Temporal Modelling of Dam Deformation Using Independent Component Analysis*. *Survey Review*. 46(339), 437 – 443.
- Hyvärinen, A., and Oja, E., (2000) *Independent Component Analysis: Algorithms and Applications*. *Neural Networks*, 13(4-5):411 – 430, 2000.
- Preston, J. (2014) *Moving Forwards: Improving Strategic Transport Planning in Wales*. Public Policy Institute for Wales, November 2014, PPIW Report No.10.
- TSC (2015) *The Transport Data Revolution – Investigation into the Data Required to Support and Drive Intelligent Mobility*, Transport Systems Catapult, March 2015.
- TSC (2015b) *Modelling for Intelligent Mobility*. Transport Systems Catapult Report on Exploring Intelligent Mobility, February 2015.

BIOGRAPHICAL NOTES

Oluropo Ogundipe is a Research Fellow at the Nottingham Geospatial Institute, University of Nottingham. She gained PhD from the University of Nottingham in 2003. Her current research focus includes the use of GNSS in forestry applications, indoor positioning, and the use of GNSS for bridge monitoring. Her research interests also include multipath mitigation, RFID positioning, augmented reality and Network RTK GPS. She has also had industry experience in the GNSS and Geomatics sector working for a GNSS equipment manufacturer and as a Land & Engineering Surveyor. She is a member of the Royal Institute of Navigation.

Global Navigation Satellite Systems (GNSS) Equipped Public Transport Buses as Information Sentinels (8209)
Oluropo Ogundipe (United Kingdom)

FIG Working Week 2016
Recovery from Disaster
Christchurch, New Zealand, May 2–6, 2016

CONTACTS

Dr. Oluropo Ogundipe
Nottingham Geospatial Institute
University of Nottingham
Nottingham
UNITED KINGDOM
Tel. +44 (0)155 82 32752
Email: oluropo.ogundipe@nottingham.ac.uk
Web site: <http://www.nottingham.ac.uk/ngi/index.aspx>

Global Navigation Satellite Systems (GNSS) Equipped Public Transport Buses as Information Sentinels (8209)
Oluropo Ogundipe (United Kingdom)

FIG Working Week 2016
Recovery from Disaster
Christchurch, New Zealand, May 2–6, 2016