Identifying Abnormal Traffic Congestion On Non-Signalised Urban Roads Using Journey Time Estimation

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ABSTRACT

This paper describes a technique for estimating vehicle journey times on non-signalised roads using 250-ms digital loop-occupancy data produced by single inductive loop detectors. The technique was assessed to see whether abnormal periods of traffic congestion (caused by accidents and special events) could be identified using the journey time estimates produced along a key urban corridor in the city of Southampton. The technique used a neural network approach to provide historical journey time estimates every 30-seconds based on the average loop-occupancy time per vehicle (ALOTPV) data collected from the detectors during the previous 30-second period.

Results showed that using the output from 8 detectors over 1149m, journey time estimates with a mean absolute percentage deviation from the mean measured speed (MAPD) of 15% were returned. These were achieved using a neural network trained on 7 days of morning peak period data.

The journey time estimates produced were presented to the control room operator in the form of a moving graph, updating every 30-seconds. Results showed that the journey time estimates identified 73% of the logged incidents on the test network during the analysis period.

BACKGROUND

In recent years, there has been a growing awareness of the problems caused by congestion in urban areas and the need to manage traffic more efficiently (*1*). Current speeds, link journey times and the location and severity of incidents are considered to be essential parameters in providing information to the driver (*2,3,4*), and as a basis for effective and efficient on-line traffic management. At present, close circuit television (CCTV) is commonly regarded as the primary medium for collecting reliable on-street information. CCTV however can only give the operator a snap-shot of conditions at a specific location whereas estimates of journey time for specific routes would provide a better overall picture of link performance.

Automatic registration plate recognition using CCTV has been successfully used to provide estimates of journey time (*5*) where networks of cameras exist. A more cost effective option would result if similar estimates could be derived from the existing inductive loops controlling the city's traffic signals.

The ability to estimate journey times accurately using loop detectors, depends on the particular format and aggregation level of the digital data produced. Several techniques have relied on the ability to obtain an accurate estimate of time-mean speed, either using direct measurements from double loop speed detectors (*6,7*) or by the relationship between flow, speed and occupancy (*8*) using single loops (*9-13*), before attempting to estimate journey time.

There is often considerable unexplained day-to-day variability in recorded journey times along the same stretch of road. The ability to train a neural network using examples of various road conditions might produce a more accurate and versatile journey time estimation tool compared to the more mechanistic time-mean speed approaches. Using flow and occupancy data related to actual measured journey times, techniques involving neural networks (*12*) and fuzzy logic (*10*) have been used to estimate journey times on signalised links.

A technique enabling video footage to be collected in synchronisation with loop-occupancy data (*14*) has led to the development of detailed databases containing vehicle loop profiles matched to measured journey times. This allows the performance of various journey time estimation techniques to be assessed in detail. This paper describes the on-street performance of a neural network based journey time estimator used to identify potential traffic incidents on a non-signalised road in Southampton, given 250-ms inductive loop data for training.

OBJECTIVES

Using the 'Average Loop-Occupancy Time per Vehicle' (ALOTPV) parameter derived every 30-seconds from SCOOT-type Urban Traffic Control (UTC) detectors (*15*):

- Develop a neural network model to estimate 30-second post-event journey times along a 1149m non-signalised road in Southampton.
- Assess the accuracy of the journey time estimates produced compared to measured journey times collected through registration plate recognition.
- Over a continuous monitoring period, determine how useful the technique was for control room operators for identifying abnormal congestion and traffic incidents.

METHODOLOGY

The methodology for extracting the ALOTPV parameter from the detector data has been described in detail (*16, 17*). Single inductive loop detectors buried in the road surface produce an analog signal which is turned into a digital signal (0/1) by a detector pad usually located in the controller. A '1' indicates the presence of metal over the loop. The vehicle-presence status of a SCOOT-type detector is checked at 250-ms intervals. The presence of a vehicle is indicated by a variable number of successive 1's, each 1 representing 250-ms of occupancy (*16*). The number of 1's produced (N) for a single vehicle is given by Equation 1.

$$N = 4 * (DL + VL)/VS \text{..Equation (1)}$$

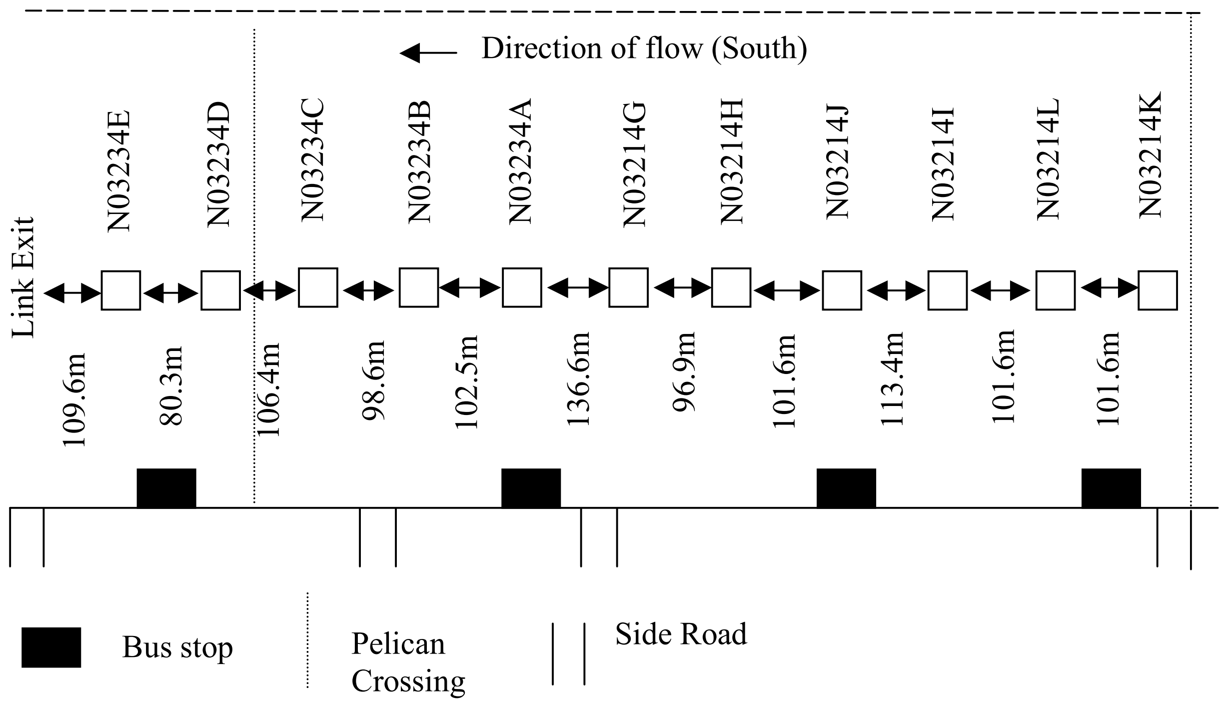
Where:
N is the loop occupancy time of the vehicle (the number of digital 1's produced, each representing 250-ms of occupancy)
DL is the detector's effective magnetic length (metres)
VL is the effective magnetic length of the vehicle (usually metallic chassis length) (metres)
VS is the vehicle speed (metres/second)

Previous research (*16*) developed the parameter of ALOTPV to help describe traffic conditions over a detector. The ALOTPV for a 30-second fixed-time interval is obtained by taking the number of 250-ms occupancies and dividing by the number of vehicles. This was engineered to return a figure of between 1 and 120, the former indicating free-flow conditions, the latter stationary traffic. All ALOTPV data used to train the neural network were collected through the ROMANSE traffic control centre in Southampton (*18*).

TEST SITE

The neural network journey time estimators were trained for operation on the A33 Bassett Avenue, Southbound inside lane (Figure 1). The A33 is a four lane un-segregated A-class road with a speed limit of 64 km/hr and had been equipped with single inductive loop detectors at approximately 100m intervals. The traffic using the road during the morning peak period (07:30 – 09:15) consists of 96% car length vehicles (3m to 4.9m) and 4% long vehicles (greater than 4.9m). Parking by the roadside is prohibited along the entire length of the test site. Two CCTV cameras are installed at either end of the link to monitor traffic and were used to confirm potential incidents detected by the neural networks.

Figure 1. A33 Bassett Avenue Southbound inside lane detectors



DEVELOPMENT OF THE NEURAL NETWORKS

The neural networks described here were built using NeuralWare's 'Predict' software (*19*) which sits within Microsoft Excel. Data are fed into the Predict model builder using Excel spreadsheets. 'Predict' not only generates a neural network based on a set of data but manipulates, transforms and selects the data before they are used. During the data analysis phase, Predict takes each available data field (ALOTPV for each detector in this instance) and determines the types of transformations which work best in combination for predicting the desired output (in this case, journey time). Transformations used include identity function, exponential function, square function, inverse function and hyperbolic tangent function. Predict's variable selection process then uses a genetic algorithm to identify subsets of the selected transformations which provide the closest matches to the target output.

The neural networks created were designed using an adaptive gradient learning rule which is a form of back propagation. Instead of using a fixed architecture for the design where the number of hidden processing layers are fixed, Predict uses a constructive method called 'cascade learning' to determine the optimum number of hidden processing layers. This can lead to different numbers of hidden layers being used between networks. Matching the vehicle registration plates, extracted from video surveillance, gave the overall journey times of the vehicles travelling down the test site. The basis for training was the ability to link the 30-second ALOTPV data to the average measured journey times of the vehicles in each 30-second start interval (Table 1).

Due to the day-to-day journey time variability observed it was decided in the first instance to give the networks a minimum of four days training data, testing on an unseen day.

Table 1. An example of the training data used as inputs to a neural network journey time estimator. (For each 30-second interval the ALOTPV values are shown at each detector site together with the average measured journey times of the vehicles in that period).

Start Interval	Detector 3214J ALOTPV	Detector 3234C ALOTPV	Measured Journey Time (secs)
08:10:00	2.3	3.8	220
08:10:30	2.4	2.9	218
08:11:00	2.4	3.0	235
08:11:30	2.6	2.7	240
08:12:00	2.3	4.2	232

In summary, the neural networks were trained by presenting them with a picture of the link conditions at each detector every 30-seconds, married to the measured journey times of the vehicles over the whole link who set off from the origin during that interval. During testing, an estimate of link journey time based on the immediate conditions was made every 30-seconds, post-event. The effects of slower vehicles exiting or entering the link would be represented in the 30-second ALOTPV values of upstream detectors, if following vehicles were also forced to slow as a direct result.

Four neural networks were designed using ALOTPV data from detectors N03214I, N03214J, N03214H, N03214G, N03234A, N03234B, N03234C, N03234D, N03234E in the inside southbound lane of the A33 Bassett Avenue (Figure 1).

'D2345' trained on ALOTPV data collected from the detectors in 1996 (22/10/96, 23/10/96, 24/10/96 and 25/10/96). The network had a 7-8-1 architecture (transformations from 7 of the detectors were used as inputs, passing through 8 hidden layers to produce the journey time output) and produced an internal correlation during training of 0.9669.

'MixTR' was a network trained on a mixture of ALOTPV data from 1996 and 2001 (22/10/96, 24/10/96, 26/02/01 and 27/02/01). This network had a 5-7-1 architecture and produced an internal correlation during training of 0.9555.

'TR001' was a network trained solely on ALOTPV data from 26/02/01, 27/02/01 and 23/11/00. This network had a 6-2-1 architecture and produced an internal correlation during training of 0.9495.

'All Days' was a network given ALOTPV data from all the available survey days for training (22/10/96, 23/10/96, 24/10/96, 25/10/96, 26/02/01, 27/02/01 and 23/11/00). This network had an 8-4-1 architecture and produced an internal correlation during training of 0.9605.

Using on-line ALOTPV data collected from the ROMANSE traffic control centre, a real-time display showing 30-second updates of estimated journey times from the four neural networks was developed. This took the form of a rolling graph displaying the current estimate of journey time from the previous 30-second period and the previous 50-minutes worth of estimates. This operator interface was tested with live data to see if the estimates could be used for identifying abnormal periods of congestion between 07:00 and 19:00, Monday to Sunday.

RESULTS

The neural network journey time estimators were tested in two ways two determine:

- The accuracy of the journey time estimates produced
- The systems ability to alert the traffic control room operator to abnormal traffic situations on the A33 Bassett Avenue test section

The accuracy of the estimates were determined by giving the neural networks new unseen data from five different days (07:30 to 09:10) when the measured journey times had been derived using registration plate matching. The performance of each network was calculated over the testing period in terms of its Mean Absolute Percentage Deviation from the Mean Measured Journey Time (MAPD). Once the MAPD had been determined on each day, a one-way analysis of variance test (ANOVA) was undertaken to see if there were any significant differences in the MAPD values produced by the four neural networks. This would help determine which set of training data produced results closest to reality.

The systems ability to identify abnormal traffic situations was tested using detector data collected during eleven separate days when traffic accidents occurred on the test site between October 2000 and November 2001. The performance of the neural networks was assessed through the control room operator's ability to identify the increased journey time associated with the start of 'abnormal' traffic conditions on the link.

ACCURACY OF THE JOURNEY TIME ESTIMATES

Table 2 shows the Mean Absolute Percentage Deviations from the Mean Measured Journey Times for each of the four neural networks by test day.

Table 2. Mean Absolute Percentage Deviations from the Mean Measured Journey Times for each of the four neural networks by test day.

Test Days	'D2345'	'MixTR'	'TR001'	'All Days'
18/7/01	18.2	18.8	18.7	17.3
19/7/01	14.0	14.8	14.1	12.6
5/11/01	17.0	16.7	17.2	16.7
6/11/01	15.7	16.6	15.8	15.1
12/11/01	12.8	12.3	15.1	13.4
Mean	**15.5**	**15.8**	**16.2**	**15.0**

The results suggested that the neural network trained on all the available training data (**'All Days'**) provided estimates of journey time with the smallest mean absolute percentage deviation from the mean measured journey times (15%).

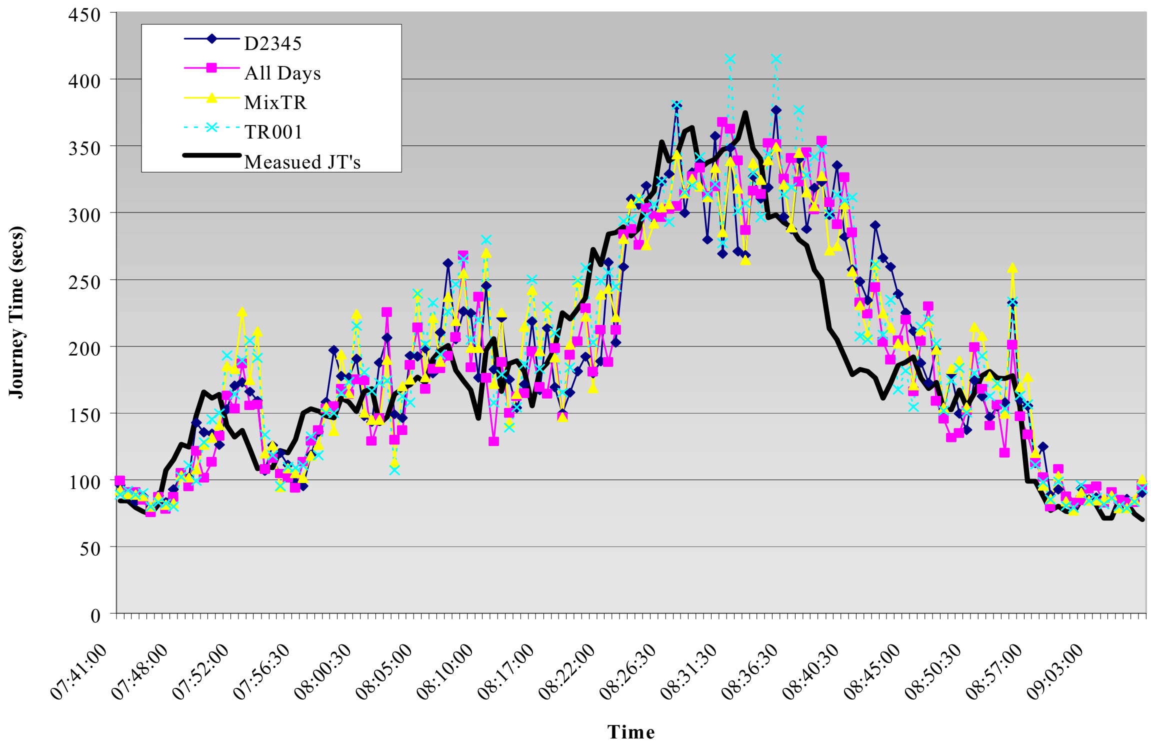
Table 3 shows the mean difference (seconds) from the mean measured journey time for each of the four neural networks by test day. The neural network trained on data from 1996 gave the smallest mean differences from the mean measured journey times (an underestimate of 2.4 seconds on average). The results from one-way ANOVA tests showed that only on the 12/11/01 were there significant differences observed between the four neural networks in terms of the mean difference from the mean measured journey times. The neural network trained on mixed data from 1996, 2000 and 2001 produced significantly smaller deviations from the mean measured journey times compared to the neural network trained solely on data from 2000 and 2001 ($F_{(3, 648)} = 3.47$, $p<0.05$)

Table 3. The mean difference (seconds) from the mean measured journey time for each of the four neural networks by test day. The results from one-way analysis of variance tests are shown.

Day	'D2345'	'MixTR'	'TR001'	'All Days'	F	$P_{(0.05)}$
18/7/01	7.0	9.3	12.3	2.4	1.36	0.25
19/7/01	-3.5	-2.4	-3.6	-6.2	0.74	0.53
5/11/01	6.3	0.6	8.4	2.7	0.63	0.60
6/11/01	-24.6	-30.5	-13.9	-20.2	2.13	0.09
12/11/01	3.0	-1.0	13.4	7.9	3.47	0.01
Mean	**-2.4**	**-4.8**	**3.3**	**-2.7**		

The journey time estimates produced for the 18/7/01 are shown in Figure 2.

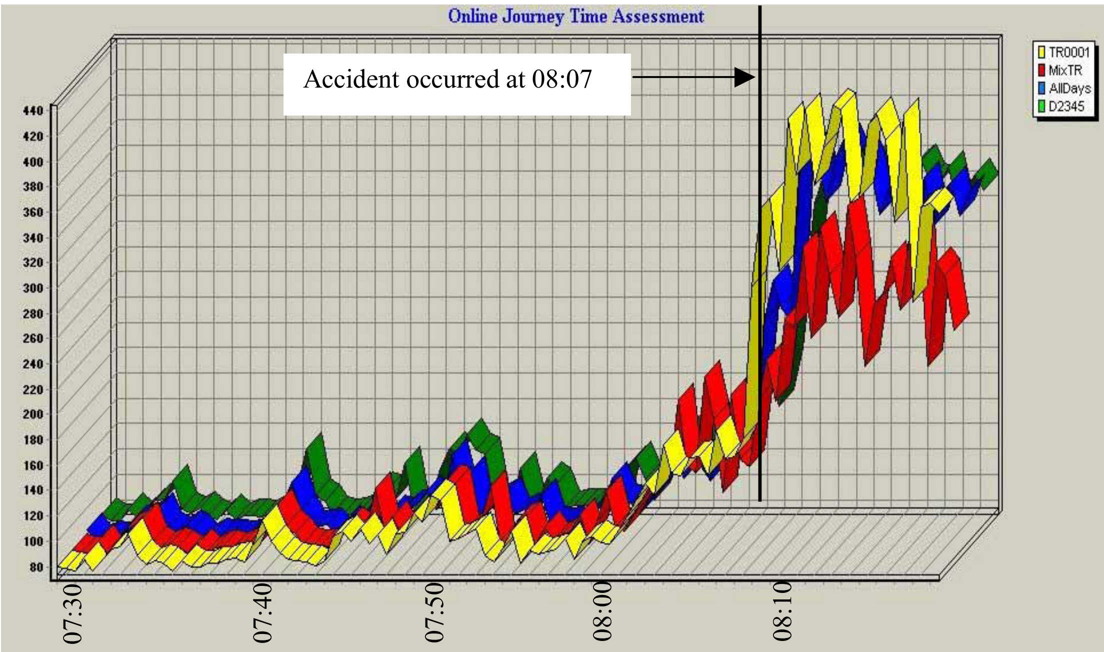
Figure 2: Journey time estimates made on the 18/7/01 along the 1149m of Bassett Avenue inside lane Southbound.



IDENTIFYING POSSIBLE TRAFFIC INCIDENTS

Between August 2000 and November 2001, 11 traffic incidents involving either vehicle-on-vehicle impacts or individual breakdowns were recorded along the A33 test section by the ROMANSE traffic control room operators. Results showed that the journey time estimates produced identified 73% of the incidents on the network during the testing period. The remaining 27% could not be identified because these incidents either occurred during off-peak periods when no congestion was caused or during already congested peak periods. A screen shot taken from the operator interface on the 27/6/01 when an accident occurred at 08:07 is shown in Figure 3.

Figure 3. Journey time estimates over the 1149m of the South bound inside lane of the A33 Bassett Avenue (27/6/01). The image is a screen-shot taken from a prototype journey time estimation operator interface.



Key to Figure 3:
X Axis = Time (30-second updates)
Y Axis = Journey Time (seconds)
'TR001' neural network = Yellow line
'MixTR' neural network = Red line
'All Days' neural network = Blue line
'D2345' neural network = Green line

The incident was logged by the police at 08:08 and was reported cleared at 09:12. A one-way ANOVA on the journey time estimates given by the four neural networks during this period showed that there were significant differences in the estimates produced ($F_{(3, 644)} = 18.01$, $p<0.001$). The neural network trained on ALOTPV data from 2000 and 2001 (TR001) returned significantly greater estimates of journey time compared to 'MixTR' which was given a combination of 1996 and 2001 data for training. This demonstrated the effects different training data had on estimation performance. A separate one-way ANOVA showed that there were significant differences in the mean measured journey times of vehicles between the days used for training ($F_{(4, 548)} = 26.2$, $p<0.001$). ALOTPV data for the 08:00 to 09:00 peak periods were compared for the days used to train MixTR and TR001. The influence of the increased congestion on 23/11/00 caused the significantly larger journey time estimates by the TR001 neural network.

Despite the differences between the estimates produced, the initial effect of the incident was picked up by all the journey time estimators, the mean journey time increasing by approximately 135% between 08:04 and 08:10. This equated to a mean reduction in average speed over the 1149m of 16 km/hr between 08:04 and 08:10.

Incidents which occurred during already congested periods were harder to identify. Unless a total road closure was caused, the journey time estimates produced by normal queuing vehicles would mask any influence a stationary vehicle might have by the side of the road. Incidents occurring during off-peak periods which failed to cause queuing over upstream detectors were also difficult to detect in the journey time estimates.

CONCLUSIONS

This paper has described a neural network based technique for estimating journey times on non-signalised roads using the 250-ms digital output produced by single inductive UTC detectors. The results showed that journey time estimates with a mean absolute percentage deviation from the mean measured journey times of 15% could be obtained over a 1149m stretch of carriageway during the morning peak period. The journey time estimates produced by four neural networks training on different combinations of morning peak time ALOTPV data showed that potential traffic incidents causing increases in congestion could be accurately identified.

The four neural networks designed in this research are unique to the road on which they were trained, containing the specific characteristics of the A33 Bassett Avenue (bus stops, pedestrian crossings and key junctions). A separate issue not addressed here is how conditions on a road change over time and how representative of 'typical' link conditions are the data that have been collected for training? How often would new training data be required to 'update' a network in order to keep pace with changing traffic conditions over time? Collecting training data using registration plate surveys is an expensive process, and a key issue is the minimum amount needed for the training process.

There is great potential for this type of detailed, immediate post-event journey time information. If estimates of journey time on non-signalised links can be coupled with similar estimates through signalised urban areas, complete routes could be monitored continuously. This has benefits both in terms of more accurate network management, (signal control, monitoring special events, incident detection) and in providing accurate driver information.

This work has emanated from the EU 5th Framework (Information Society Technologies Programme) PRIME project, (**P**rediction of congestion and incidents in **R**eal time, for intelligent **I**ncident **M**anagement and **E**mergency traffic management) (*20*).

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