COMPARISON OF PREDICTION METHODS FOR URBAN NETWORK LINK TRAVEL TIMES

Joanna K. Hartley
School of Computing and Mathematics, The Nottingham Trent University
Burton Street, Nottingham, NG1 4BU, U.K.
Tel. +44 (0) 115 848 6172, Fax. +44 (0) 115 848 6518
Email: Joanna.Hartley@ntu.ac.uk

KEYWORDS
Transportation, Optimisation, Efficiency, Prediction methods.

ABSTRACT

Traffic congestion is becoming a serious environmental threat that must be resolved quickly. The mobile travel information system developed at The Nottingham Trent University enables the integration of data concerning traffic flows and individual journey plans thus making it possible to perform optimisation of travel. This paper focuses on the issue of provision of real-time information about urban travel and assistance with planning travel. Nottingham's SCOOT (Split Cycle Offset Optimisation Technique) traffic-light control system provides real-time information about the link travel times within certain areas of the city. However, rather than using link travel times at the time of the request, it is more effective to predict the link travel times for the time of travel along the particular links. The future link travel times depend upon the historical travel time of the link (for the specific time step in the day) as well as the current link travel time. Consequently, the link weights are a combination of real-time data, historical data and static data. Three prediction methods have been implemented and tested in the context of Nottingham's urban road network. The preliminary results suggest that the information discounting technique gives the best results.

BACKGROUND

Traffic congestion is becoming a serious environmental threat that must be resolved quickly. Great Britain has become a role model in the battle against global pollution. The Prime Minister, Tony Blair, has acknowledged that a 20% reduction in carbon dioxide emissions in Great Britain is a credible target for the year 2010 (Brown, 1997). However, significant measures are necessary to attain this target. Road vehicles and industry are the main sources of pollutant emissions. In the United Kingdom, road vehicles are responsible for over 50% of the emissions of nitrogen oxides and over 75% of carbon monoxide emissions (DETR, 1998). Congestion is already a major problem in many areas and traffic volume is set to grow by 30% in the next 20 years (MacAskill, 1999).

This paper describes the infrastructure that is currently being developed at The Nottingham Trent University to facilitate multi-modal travel throughout the city of Nottingham. This paper focuses on the issue of provision of real-time information about urban travel and assistance with planning travel. This includes consideration of uncertainty about traffic delays, inconvenience of parking and the variability of travel time along urban links.

TRAVEL INFORMATION SYSTEMS

There are a number of ways of informing travellers about the location of congestion areas – such as, radio or television broadcast and variable message signs. The growing body of opinion, that the traditional forms of supervisory control are both too expensive and inaccurate, prompts new development. The traditional forms require full involvement of a human operator. However they do not take into account the specific requirements of individual journeys. In particular, because of the protection of privacy, the crucial information about the intended destinations of individual vehicles is not normally available to these controllers and, even if it was, it could not be processed efficiently. On the other hand, an attempt to delegate the responsibility for journey optimisation to road users by informing them (through radio broadcasts or variable message signs) about the best routes, that are relevant to various journeys, is bound to be counterproductive because of the resulting information overload.

To eliminate these constraints, this research project takes a fundamentally different approach and rather than aiming at maximising the efficiencies of the use of individual modes of transport taken in isolation, it considers a broader multi-modal travel framework. Travel requirements are defined in terms of journeys and the mode of travel is just one of the decision variables. An important feature of our approach is that it recognises the individual nature of journeys. The enquirers are able to select their journey according to their individual preferences, such as the importance of

Proceedings 15th European Simulation Symposium
Alexander Verbraeck, Vlatka Hlupic (Eds.)
(c) SCS European Council / SCS Europe BVBA, 2003
ISBN 3-936150-28-1 (book) / 3-936150-29-X (CD)

a short journey time or the importance of timely arrival at the destination. Although the answers may be highly subjective it must be remembered that it is precisely these preferences that make people opt for one mode of transport or another. In this sense, multi-modal travel optimisation offers good mapping onto human decision-making.

Travel information systems are now being developed which incorporate route guidance systems to divert drivers away from the congested areas either by change of travel mode or travel route. Dynamic guidance is of the greatest benefit to travellers, as new routes and travel modes can be suggested as conditions change (McDonald and Montgomery, 1996). The system will aid the road users by providing access to information that is not readily observable form the current location of the traveller, yet is relevant because of the planned journey. The wide use of such a system will reduce the amount of congestion within the city, by the choice of departure time and shorter routes as suggested by the route guidance system. This will lead to expected reductions of pollutant emissions in currently congested and critical areas.

The system must be capable of simultaneous data acquisition, processing and dissemination of the traffic/travel advice in real-time to a full spectrum of end users. Preston et al. (1993) proposed the use of in-vehicle telephones to communicate with a remote computer. The increasing use of mobile phones by the general public takes their suggestion one step further, opening access to the decision support system to many more users. The integration of data concerning traffic flows, public transport and individual journey plans thus makes it possible to perform multi-modal optimisation of travel.

The system enables progression from a passive mode of interaction between traffic control systems and road-users (one-way flow of information) to an active mode. Within the active mode, the road users supply the information about their intended destination (without disclosing their identity) and, in response, receive customised traffic information that optimises their journeys.

So, there is a need for a hierarchical urban sustainability structure that would be specifically responsible for providing a global optimisation layer while relying on the local optimisations affected by the individual organisations responsible for urban transport (Peytchev and Bargiela, 1998; Pursula, 1998). The development of such a structure should clearly rely to a maximum extent on the standard computer and public communication systems. However, the feasibility of such an undertaking has to be proven by detailed consideration of the technological constraints of the sub-systems that are to be integrated.

The developed structure is a Distributed Memory Environment (DIME) (Peytchev and Bargiela, 1998) that manages the data from a number of sources (Traffic Control Centre, public transport company and the user) (Figure 1). Nottingham Traffic Control Centre continues its kind agreement of allowing the Intelligent Simulation and Modelling group to have access to its Traffic Control System (SCOOT and congestion data), providing the necessary current traffic information. Nottingham City Transport has obligingly approved the use of the necessary information concerning their bus timetables.

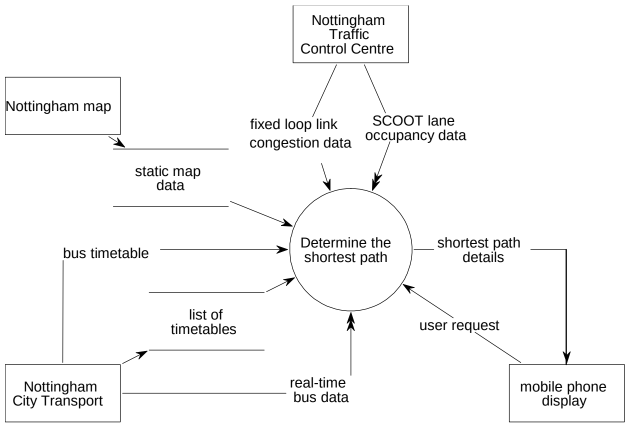


Figure 1: Determining the Shortest Path

The user communicates with the DIME system via a mobile phone. The advantage of a mobile phone is that there do not exist the constraints of being part of a private vehicle’s equipment or being deployed at a particular location. Along with the increasing use of mobile phones by the general public, this means that the system has a much broader user base. By implication, this will result in a much greater impact on travel mode switching decisions (Bargiela and Berry, 1999). Also, the system is easy to use and not prohibitively expensive.

ROUTE GUIDANCE

There are many methods of path finding that are appropriate for use within the spectrum of route guidance. Some of these methods have been considered and evaluated in the context of multi-modal travel in Nottingham’s urban network. The results are published in (Hartley and Bargiela, 2001; Hartley, 2003a). This paper concentrates on the delivery of timely route guidance given the available real-time traffic information. This involves the prediction of traffic. Three prediction methods will be presented, and tested using private vehicle real-time traffic data. However, any of these prediction methods may also be used in the context of public transport and multi-modal travel.

Urban Network Information

In the context of private vehicle travel, the pre-requisite to determining any shortest path in an urban network is having information about the road link weights (Figure 2).

The necessary input data, mostly provided by the different organisations managing the urban network, comprises SCOOT (Split Cycle Offset Optimisation Technique) link data, congestion data for fixed loop links and static map data (Figure 1).

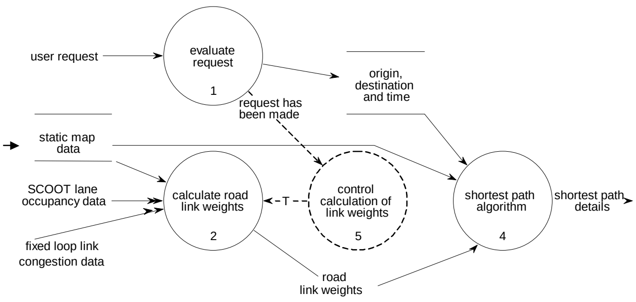


Figure 2: Calculation of Travel along Links

SCOOT is an intrinsic part of Nottingham's traffic-light control system comprising induction loops that detect the presence of vehicles in real-time. The SCOOT link data provide real-time information about the link travel times within certain areas of the city. Fixed loop congestion data again provide real-time information – these data are specific to certain junctions or roads (distinct from the SCOOT-managed areas). The static map data include information about the topology of the urban network and the length of roads. The integration of SCOOT lane occupancy data (leading to link times in SCOOT-managed areas), fixed loop congestion data (leading to link times in some non-SCOOT areas) and static map data (providing estimated static data of the link times for the remainder of the network) are manipulated into up-to-date, reliable information of alternative paths and adverse traffic conditions on appropriate links. This enables the derivation of the optimal route for travel by private vehicle.

Travel by Private Vehicle

Dijkstra's algorithm (1959) has been used to determine the optimal route by private vehicle. Dijkstra's algorithm builds an expanding list of examined vertices and looks at paths through vertices on the list. The path with the smallest total of link weights is incrementally found.

Dijkstra's algorithm

```
pathlength(all links) = ∞
marked(all links) = .false.
marked(origin) = .true.
pathlength(origin) = 0
do for all links until marked(destination) = .true.
  {
  search for all pairs of nodes s.t.
  marked(node1) = .true. & marked(node2) = .false.
  then
     pathlength(node2) = min(pathlength(node2),
              pathlength(node1)+length(node1,node2));
     from this set determine which node2 has minimum
     pathlength then
        marked(node2) = .true.
  }
```

PREDICTION OF LINK TRAVEL TIMES

Rather than using link travel times at the time of the request, it is more effective to predict the link travel times for the time of travel along the particular links. The method used was developed as part of the Ali-Scout project (Kotsopoulos and Xu, 1993). The future link travel times depend upon the historical travel time of the link (for the specific time step in the day) as well as the current link travel time. The process is as follows:

$$D = \frac{T_h(l,n)}{T_{cur}(l,n)} \qquad (1)$$

where $T_h\ (l,n)$ is the historical mean travel time of link l at time step n
and $T_{cur}\ (l,n)$ is the current (time step n) travel time at link l.

$$T_p(l,m) = \frac{T_h(l,m)}{D} \qquad (2)$$

where $T_p\ (l,m)$ is the predicted travel time of link l at future time step m.

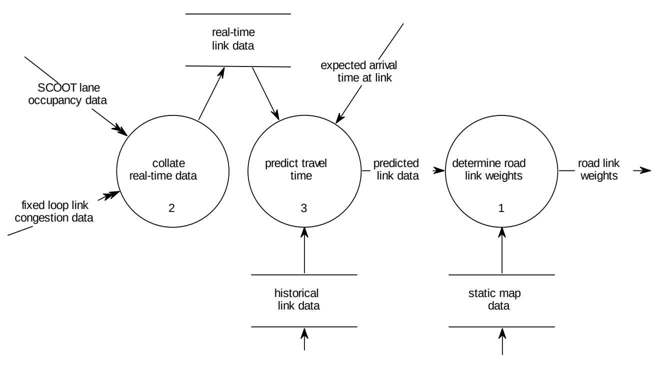


Figure 3: Combination of Historical, Current and Static Data

Consequently, the link weights are a combination of real-time data, historical data and static data (Figure 3).

Information Discounting

As the state of the network can change extensively in a short period of time, a combination of real-time data and historical data should be used, with the proportions dependant on the expected time taken to arrive at the measured link (Kotsopoulos and Xu, 1993). Kotsopoulos and Haiping (1993) propose information discounting:

$$T_{dis.}(l,m) = a * \frac{T_h(l,m)}{D} + (1-a) * T_h(l,m) \qquad (3)$$

where $T_{dis.}$ *(l,m)* is the predicted travel time of link *l* at future time step *m* using the information discounting method, and where *a* is a decreasing function of *(m-n)*, say $e^{-k(m-n)}$. An appropriate choice of *k* will lead to accurate predictions. For 10<*k*<90, the point at which historical data has more influence than current data ranges from ten minutes to one hour into the future.

Resolution of Data

Abdulhai et al. (1999) argue that the level of data aggregation should be comparable to the prediction horizon for best accuracy. The method is an adaptation of the Ali-Scout information discounting method.

$$D_m = \frac{\sum_{i=2n-m-1}^{n} T_h(l,i)}{\sum_{i=2n-m-1}^{n} T_{cur}(l,i)} \qquad (4)$$

D_m is the ratio between the historical information aggregated over the previous time period of *(m-n)* and the most recently collected information aggregated over the same time period.

$$T_{res.}(l,m) = a * \frac{\sum_{i=n+1}^{m} T_h(l,i) \big/ (m-n)}{D_m} + (1-a) * \frac{\sum_{i=n+1}^{m} T_h(l,i)}{m-n} \qquad (5)$$

$T_{res.}(l,m)$ is the predicted travel time of link *l* at future time step *m* using a resolution of data that is comparable to the prediction horizon.

Prediction Updating

The prediction of events in the near future is often considered to be highly related to recent past events. However, when determining predictions in the longer future, this correlation often decreases. The use of predictions in the near future to determine predictions in the longer future results in an iterative process.

$$T_{iter.}(l,m) = a * \frac{T_h(l,m)}{D^p_{m-1}} + (1-a) * T_h(l,m) \qquad (6)$$

$$D^p_{i:i>n} = \frac{T_h(l,i)}{T_{iter.}(l,i)} \qquad (7)$$

$$D^p_n = \frac{T_h(l,n)}{T_{cur}(l,n)} \qquad (8)$$

$T_{iter.}(l,m)$ is the predicted travel time of link *l* at future time step *m* using prediction updating. D^p_i is the ratio between the historical information and the predicted travel time (for a specified time period in the day, *i*).

REAL URBAN TRAFFIC NETWORK APPLICATION

Currently, the available real-time information in the Nottingham urban network is collected from SCOOT detectors, which monitor highly traversed links within the city centre and the arterial routes into the city. 100 links out of 2018 are currently equipped with SCOOT inductive loop detectors. The SCOOT data consists of a large amount of traffic control information relayed in the form of messages (Siemens PLC, 1997) (which include information about flow, occupancy, delay and speed etc.). The U06 message provides information every 30 seconds about the average point-speed of a private vehicle travelling along a link (measured over the last 5 minutes). This speed and knowledge of the link length is used to estimate the current travel time of the link. As some of the routes across Nottingham may take up to one hour to traverse, it is not sufficient to use the current travel time estimations (Hartley, 2003b). So, instead predictions of travel time are used (as described in section 3.2).

RESULTS

The available historical U06 messages will be used to determine the validity of the prediction method in the context of Nottingham's urban network. The results will also show how the incorporation of real-time information routes traffic away from congested areas. It will also be determined how capable the methods are in dealing with the transition between peak and off-peak conditions.

Figures 4 and 5 show that the historical speed cannot be relied upon, as the speeds fluctuate even within a short period on a single link on a single day.

Figure 4. Average speed every 30 mins on link N11531C

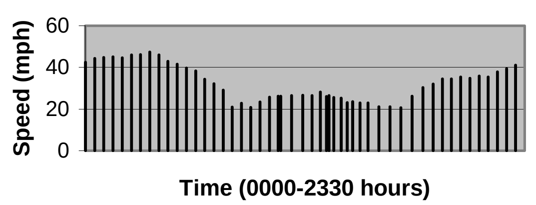
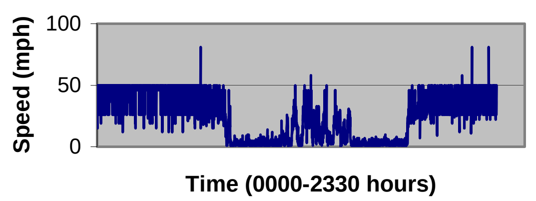


Figure 5. Actual speed of link N11531C over one day



The efficiency of the algorithm is of paramount importance, so that the information provided to the user is timely and thus relevant. For Nottingham's network of 597 nodes and 2018 links, Dijkstra's algorithm has a system run-time of 0.4 seconds. The execution time of the predictive route finder algorithm should not be greater than a few seconds.

Information Discounting

Using k=1/60, Kotsopoulos' (1993) information discounting method gives the following results (Figure 6), where one step is equivalent to 30 seconds.

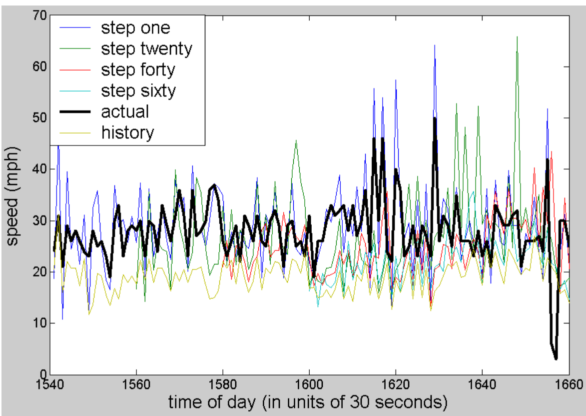


Figure 6: Ali-Scout Prediction with Information Discounting

The mean square error (MSE) between the actual speed and predicted speed is presented in Table 1. The methods have also been tested to determine how they cope with incidents.

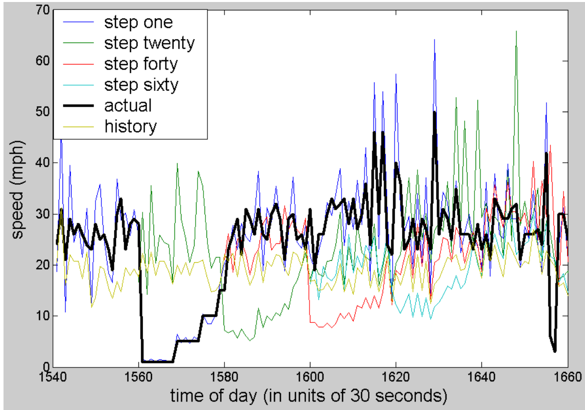


Figure 7: Prediction using Ali-Scout with Information Discounting after an Incident

Figure 7 shows that the information discounting method lessens the effect of the incident as the prediction moves further into the future. The MSE between the actual speed and predicted speed is shown in Table 2.

Resolution of Data

Data resolutions that are comparable to the prediction horizons have been used in conjunction with the Ali-Scout (with information discounting) prediction method. Figure 8 shows how the results show much less fluctuation as the step size increases. Figure 9 shows that after an incident, the prediction method is considering data prior to the incident (as part of its averaging process) and consequently poor performance is shown. The MSE between the actual speed and predicted speed in both cases are shown in Tables 1 and 2.

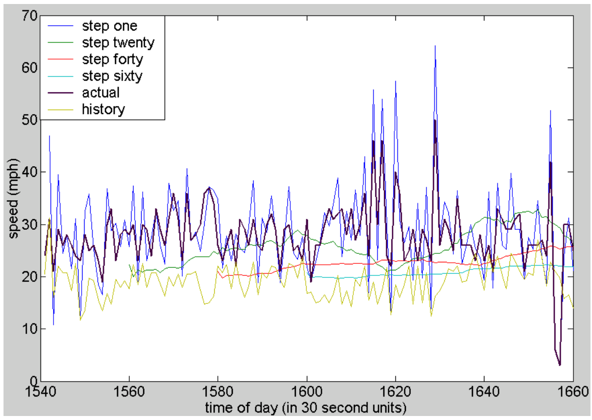


Figure 8: Prediction with Data Resolution

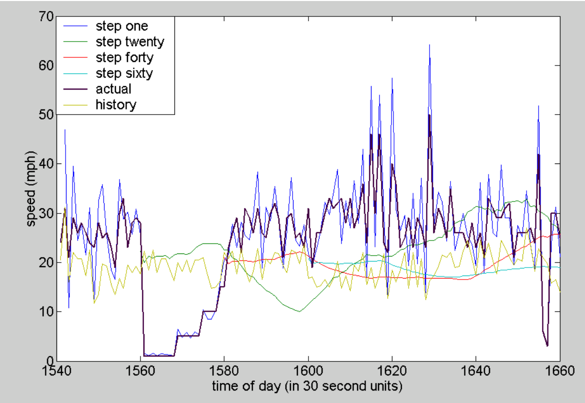


Figure 9: Prediction with Data Resolution after an Incident

Prediction Updating

The iterative process using predictions for the near future will be implemented to determine larger prediction horizons. Clearly this method is more time-consuming than the previous two methods as numerous calculations are required as part of the iterative process. Figure 10 shows that the method tends to severely underestimate the actual value.

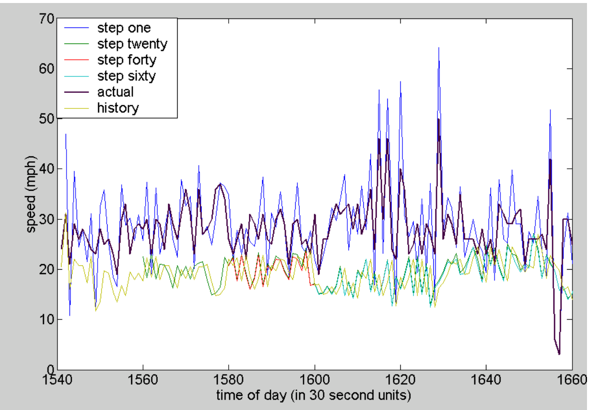


Figure 10: Prediction using an Iterative Process

In a similar manner to the data resolution method, Figure 11 shows that after an incident, the iterative method is considering data prior to the incident (as part of its iterative process) and consequently poor performance is shown. In fact, there is little evidence of the predicted data being influenced at all by the incident. Again, the MSE between the actual speed and predicted speed in both cases are shown in Tables 1 and 2.

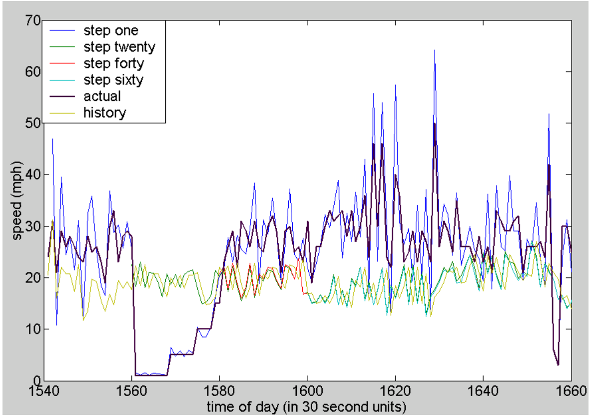


Figure 11: Prediction using an Iterative Process after an Incident

Table 1: The Mean Square Error between the Actual Speed and Predicted Speed

	Prediction method			
Step number	Historical	Information Discounting	Resolution of Data	Prediction Updating
One	151.1	42.5	42.5	42.5
Twenty	151.1	51.8	84.5	161.45
Forty	151.1	53.8	84.3	169.72
Sixty	151.1	89.5	113.6	192.72

Table 2. The Mean Square Error between the Actual Speed and Predicted Speed after an Incident

	Prediction method			
Step number	Historical	Information Discounting	Resolution of Data	Prediction Updating
One	160.5	40.0	40.0	40.0
Twenty	160.5	51.6	155.9	174.18
Forty	160.5	53.1	124.3	169.76
Sixty	160.5	89.5	146.4	192.72

DISCUSSION

The above clearly show that the Ali-Scout prediction method with information discounting alone gives the best results. The resolution of data method gives better results than the historical information in all cases, while the prediction updating method gives worse results. A value of k=1/60, as part of the information discounting calculation, was used in all cases. Recalibration of this value may give better results for each of the methods.

CONCLUSIONS

The Ali-Scout information discounting prediction method (Kotsopoulos and Haiping, 1993) has been shown to be more reliable than historical information in the context of link travel times in Nottingham's urban transport network. The difference is significant when predicting travel times up to 40 minutes ahead of time. This prediction method has been shown to be capable of dealing with incidents.

This paper demonstrates the necessity of real-time information when providing traffic/travel information to the general public. The use of real-time data provides the user with information about the state of the network, not normally foreseeable by the traveller.

It should be noted that minimisation of travel time by private vehicle does not necessarily produce the optimal route from 'door-to-door'. With the increasing ownership of private vehicles, there is more demand on the limited number of parking spaces within any city. Consequently, the inconvenience of parking can make travel by private vehicle be less preferable especially for those travellers who are particularly adverse to travel time uncertainty. So users may ultimately be encouraged to travel by public transport instead. This becomes especially apparent when travel advice includes both private vehicle and public transport as modes of transport, as is the case in the developed real-time travel information system detailed in section 2.

FUTURE WORK

Studies have shown that the acceptance of route guidance is strongly correlated to any previous experience of the system. Simulation (Peytchev and Bargiela, 1995) will be used to test how the use of the route guidance system will enhance the progression of the traveller (McDonald et al., 1995).

Due to the large amounts of static and real-time data that will be used by the path finding algorithm, there are a number of issues to investigate with regard to storing information. The appropriateness of storing set paths, or calculating paths on demand will be investigated. The pruning of the urban network will be necessary – this may be achieved in a pre-processing mode or as part of the algorithm. Also, further analysis of multiple users (of the order of 100) will need to be considered to continue to provide a viable service. Some possible long-term solutions are the use of more processors, parallel algorithms, or some form of artificial intelligence (such as neural networks).

The inherent fluctuation of both past and future travel times along links means that any predicted travel times are subject to uncertainty. Consequently, an extension of the prediction method to determine confidence intervals will be considered in the future.

REFERENCES

Abdulhai, B., Porwal, H., Recker, W., 1999. "Short Term Freeway Traffic Flow Prediction Using Genetically-Optimized Time-Delay-Based Neural Networks", *California PATH Working Paper*, ISSN 1055-1417.

Bargiela, A., Berry, R., 1999. "Every BIT counts", *Traffic Technology International*, Feb/Mar, pp 63-66.

Brown, P., 1997. "Britain's Green Lead at UN", *The Guardian*, 24 June 1997.

DETR, 1998. "Air Pollution – What it Means for Your Health", Air and Environmental Protection, http://www.environment.detr.gov.uk/airq/aqinfo.htm.

Dijkstra, E.W., 1959. "A Note on Two Problems in Connection with Graphs", *Numerishe Mathematic*, 1, pp 269-271.

Hartley, J.K., 2003a. "Efficiency vs. Correctness of a Travel Information System", *Proc. UKSim 2003*, April 2003, ISBN 1-84233-088-8, pp 214-219.

Hartley, J.K., 2003b. "Prediction of Link Travel Times in the Context of Nottingham's Urban Road Network", *Proc. of 17th European Multi-Conference*, Nottingham, June 2003, ISBN: 3-936150-25-7, pp 423-428.

Hartley, J.K., Bargiela, A., 2001. "Decision Support for Planning Multi-Modal Urban Travel", *Proc. of 13th European Simulation Symposium*, Marseille, October 2001, ISBN: 90-77039-02-3, pp 387-391.

Kotsopoulos, H.N., Haiping, X., 1993, "An Information Discounting Routing Strategy for Advanced Traveller Information Systems", *Transportation Research Part C*, Vol. 1, No. 3, pp 249-264.

MacAskill, E., 1999. "Promise of a better, faster, more reliable system", *The Guardian*, 14 December 1999.

McDonald, M., Hounsell, N.B., Njoze, S.R., 1995, "Strategies for Route Guidance Systems Taking Account of Driver Response", *Pacific Rim Trans. Tech. Conf., 1995 Vehicle Navigation and Info. Systems Conf. Proc. 6th International VNIS*, pp 328-333.

McDonald, M., Montgomery, F.O., 1996. "Urban Traffic Control In Europe", *Proc. Instn. Civ. Engrs. Transp.*, Vol. 117, February, pp 50-56.

Peytchev, E., Bargiela, A., 1995, "Parallel Simulation of City Traffic using PADSIM", *Proceedings of Modelling and Simulation Conference ESM'95*, Prague, Eds. Snorek, Suhansky, Verbraeck.

Peytchev, E., Bargiela, A., 1998. "Traffic Telematics Software Environment", *Proc. European Simulation Symposium*, Oct. 1998, ISBN 1-56555-147-8, pp 378-382.

Polenta, T., Hartley, J.K., 2003. "A comparative Study of Stochastic 'Least-Time' Path Algorithms in the Context of the Nottingham Urban Network", *Proc. UKSim 2003*, April 2003, ISBN 1-84233-088-8, pp 194-200.

Preston, J.M., May, A.D., Aldridge, D.M., 1993, "The Specification of Trip Planning Systems", *IEE Colloquium on 'Electronics in Managing the Demand for Road Capacity'*, pp 2/1-4.

Pursula, M., 1998. “Simulation of Traffic Systems - An Overview”. *Proc. 10th European Simulation Symposium*, Nottingham Trent University, October 1998, pp 20-24.

Siemens PLC, 1997. ‘SCOOT User Guide’, Poole, Issue 17.

AUTHOR BIOGRAPHY:

JOANNA HARTLEY was awarded a BSc (Hons) degree in Mathematics at the University of Durham in 1991. In 1992, she became a research assistant in the Department of Computing at The Nottingham Trent University and was awarded a PhD in 1996. The title of her PhD is “Parallel Algorithms for Fuzzy Data Processing with Application to Water Systems”. She is now a senior lecturer at The Nottingham Trent University and an active member of the Intelligent Simulation and Modelling group. She is a member of the UKSim committee and was an associate editor of UKSim 2003 and a member of the organising committee for ESM’03. Her current research interests include parallel processing, mathematical modeling and probabilistic state estimation relating to urban traffic networks and water distribution systems.