LOCATION-BASED SERVICES FOR IN-VEHICLE ROUTE GUIDANCE WITH REAL TIME TRAFFIC INFORMATION

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ABSTRACT

This paper intends to model the determination of best path in transportation networks with real-time and stochastic traffic information. Although real world in-vehicle route planning problems are dynamic and real-time traffic information is among the most important and essential criteria for drivers during route selection, most current systems have been based on static algorithms. In this paper, the theoretical concepts of real-time in-vehicle route planning are discussed and a model is proposed. In the modeling process, a location based service (LBS) for in-vehicle route guidance system using real-time traffic information is proposed and implemented in a mobile GIS environment.

Keywords: *Location based service, Route planning, Real-time traffic information*

1. INTRODUCTION

Route planning algorithms are one of the most important components of In-Vehicle Route Guidance Systems (IRGS) in Intelligent Transportation Systems (ITS). Although real world in-vehicle route planning problems are dynamic and real-time traffic information is one of the most important and essential criteria for drivers during route selection, most current systems have been based on static algorithms. Recent developments in information and communication technologies (ICT) and their impact on transportation researches lead to intelligent transportation systems (ITS). In many countries there is a traffic control centre which is a part of their intelligent transportation systems, and it is the unit where ITS applications and tools are developed and traffic information are collected through the use of various methods. We assume that the traffic information of each link is available in real-time. This information is provided through Advanced Transportation Management Systems (ATMS) such as inductive loop detectors, magnetometers, microwave radar sensors, infrared sensors, ultrasonic sensors and video image processor of traffic cameras. By using the collected data from these sensors, traffic information like traffic volume and average vehicle speeds (AVS) are determined. This information can be used effectively to manage transportation problems and to reduce congestions. This information can also be used to help drivers determining their route to destination at the least time.

The classical route guidance systems assume the deterministic environment in which the shortest path (SP) problem in terms of travel distance, travel time, travel cost, or a combination of the deterministic attributes have been intensively used (Ying et al., 2008). Many efficient algorithms have been developed for deterministic routing (Bellman, 1958; Dijkstra, 1959; Dreyfus, 1969; Hart et al., 1968). These algorithms are referred to as the standard shortest path algorithms. However, in real world situations the assumption of deterministic and time independent traffic information is not valid and different kinds of uncertainties could often arise from various sources such as link capacities during the peak and non-peak hours, failure, maintenance and Seasons' variations. These uncertainties lead to travel time variability which can be modelled by their distribution functions. In order to reduce these uncertainties, the assumption of stochastic and time-dependent traffic information for each link must be taken into account. The question is that how should one incorporate the travel time variability and its distribution in route planning?

Many algorithms exist for finding the least expected travel time path through networks with deterministic and time-dependent travel times (e.g., Dreyfus 1969) and for finding the least expected travel time path through networks with stochastic and time-independent travel information (e.g., see Dijkstra 1959). The question of how to find the least expected travel time path through a network with travel times that are both stochastic and time-dependent and the real world implementation of it are still subject to a broad range of researches (Fu and Rilett, 1998; Hall, 1986; Ji, 2005; Miller-Hooks and Mahmassani, 2000; Park et al., 2010). A recent literature review can be found in (Abdel-Aty and Abdalla, 2006; Gao and Chabini, 2006). Without the assumption of real-time variability of traffic information of network, the previous researches mostly have adapted a standard shortest path algorithm to find the minimum expected travel time path, under a stochastic and time dependent situation.

In this paper the aim is to introduce a model for in vehicle route guidance system using real-time traffic information. The assumption is that traffic information is real-time, stochastic and time dependent which means that for each link, real-time traffic information are available and depends on the time of arrival of that vehicle to that link and also the variations in the traffic of each link do not follow a systematic rule.

Regarding these assumptions, we intend to present a location based service which helps the driver to find the best route regarding real-time situation of the network. The model provide the driver with the next best link when he needs help and defer other best links, towards the destination, until arrival to that links. With this strategy, the driver can incorporate his expertise in route planning and select the best route based on his knowledge. When he cannot decide on choosing between some links, the system incorporating real-time traffic of subsequent links and real-time as well as historical traffic of other links, determines the next best link.

The rest of the paper is organized as follows: Section 2 contains an overview of the materials and methods used in this research including description of the real-time, stochastic and time-dependent route planning problem and its formulation. Section 3 presents an illustrative example and in Section 4; the implementation of the model is described and illustrated. Section 5 provides a discussion about the proposed model and the implemented system and finally in section 6, conclusions and future directions for the research are discussed.

2. REAL-TIME, STOCHASTIC AND TIME-DEPENDENT ROUTE PLANNING

In order to formulate the route planning under stochastic and time dependent real-time traffic information, a directed acyclic graph, $G = (N, A)$, is defined with a finite set of nodes, $N = \{n_1, n_2, \cdots, n_n\}$, a set of arcs, A, a current decision node, $i \epsilon N$ and a target node (destination), $d \epsilon N$, (Figure 1).

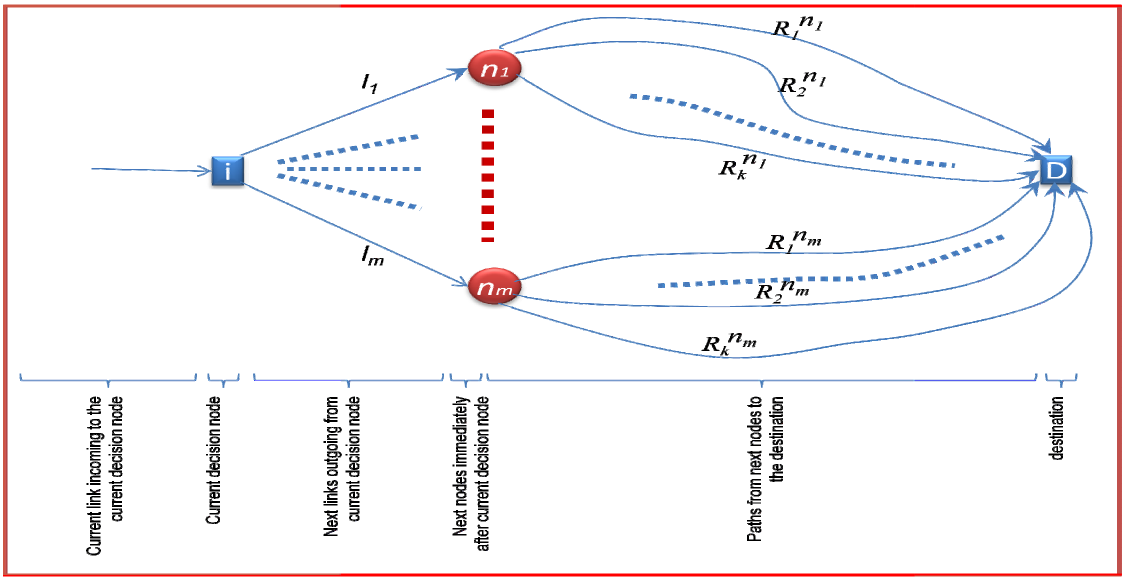


Figure 1 – Schematic network with real-time stochastic and time dependent traffic information

The model in this paper proposed an alternative algorithm for a link-based route guidance. Using the model, based on the minimization of the expected minimum travel time in each decision point (intersection), the next best link toward the destination will be determined and proposed to the driver according to the Equation 1.

$$\begin{aligned}\text{Best Link} = \ & \operatorname{argmin} \{L_1 + E[\min(R_1^{n_1}, R_2^{n_1}, \dots, R_k^{n_1})],\ L_2 \\ & + E[\min(R_1^{n_2}, R_2^{n_2}, \dots, R_k^{n_2})], \dots, L_m + E[\min(R_1^{n_m}, R_2^{n_m}, \dots, R_k^{n_m})]\}\end{aligned} \tag{1}$$

where $L = \{l_1, l_2, \cdots, l_m\}$ is the set of real-time travel time of outgoing links for current decision node (intersection), $R = \{R_1^{n_m}, R_2^{n_m}, \dots, R_k^{n_m}, R_1^{n_m}, R_2^{n_m}, \dots, R_k^{n_m}, \cdots, R_1^{n_m}, R_2^{n_m}, \dots, R_k^{n_m}\}$ is the set of time dependent random variables indicating the travel time of paths from the next nodes immediately after the current decision node (intersections) to the destination and E represents the mathematical expectation function.

Although, most of the sensors can determine the current speed of the vehicles, some of them may count number of vehicles in a specified time interval. However, in the either case, the current average travel time for a vehicle on each link can be calculated. In the first case, this can readily be done by using the length of each link divided by the current average speed of the vehicles on that link. In the last case, a volume-delay function (VDF) such as the one developed by Bureau of Public Roads (BPR) can be used to calculate the average travel time on each link (Equation 2)(Spiess, 1990).

$$S_l(v_l) = t_l\left(1 + 0.15\left(\frac{v_l}{c_l}\right)\right) \tag{2}$$

where, t_l is free flow travel time on link l per unit of time, v_l is volume of traffic on link l per unit of time (flow attempting to use link l), c_l is the capacity of link l per unit of time and $S_l(v_l)$ is the average travel time for l vehicle on link l. the current average travel time is used in Equation 1.

In order to solve the Equation 1, mathematical expectation of minimum of some random variables must be determined.

Lemma1. For two random variables, R_1 and R_2, with the expected values of μ_{R_1} and μ_{R_2} and probability distribution functions of $f_{R_1}(z)$ and $f_{R_2}(z)$ and cumulative distribution functions of $F_{R_1}(z)$ and $F_{R_2}(z)$, mathematical expectation of minimum of them can be determined using Equation 3.

$$E(\min(R_1, R_2)) = \mu_{R_1} + \mu_{R_2} - \int_{-\infty}^{+\infty} f_{R_1}(z).F_{R_2}(z).z.dz - \int_{-\infty}^{+\infty} f_{R_2}(z).F_{R_1}(z).z.dz \tag{3}$$

Proof. Considering a random variable $z = \min(R_1, R_2)$, its expectation can be determined using Equation 4.

$$E(z) = \int_{-\infty}^{+\infty} f(z).z.dz \quad => \; E(\min(R_1, R_2) = \int_{-\infty}^{+\infty} f_{\min(R_1,R_2)}(z).z.dz \tag{4}$$

To solve the Equation 4, $f_{\min(R_1,R_2)}$ is needed. Using the definition of cumulative distribution function and assuming that R_1 and R_2 are independent, $F_{\min(R_1,R_2)}$ can be calculated using Equations 5 to 7.

$$\begin{aligned}
&F_X(x) = P(X < x) => \\
&F_{\min(R_1,R_2)}(z) = P(\min(R_1, R_2) \le z) = 1 - P(\min(R_1, R_2) \ge z) \\
&\qquad = 1 - [P(R_1 \ge z) and\, P(R_2 \ge z)] \\
&\qquad = 1 - [P(R_1 \ge z).P(R_2 \ge z)] \\
&\qquad = 1 - \left[\left(1 - P(R_1 \le z)\right).\left(1 - P(R_2 \le z)\right)\right] \\
&\qquad = 1 - \left[\left(1 - F_{R_1}(z)\right).\left(1 - F_{R_2}(z)\right)\right] \\
&\qquad = F_{R_1}(z) + F_{R_2}(z) - F_{R_1}(z).F_{R_2}(z)
\end{aligned} \tag{5}$$

Using the definition of probability distribution function, $f_{\min(R_1,R_2)}$ can be calculated using Equations 6.

$$\begin{aligned}
&f_X(x) = \frac{dF_X(x)}{dx} => \\
&f_{\min(R_1,R_2)}(z) = \frac{dF_{\min(R_1,R_2)}(z)}{dz} = f_{R_1}(z) + f_{R_2}(z) - f_{R_1}(z).F_{R_2}(z) - f_{R_2}(z).F_{R_1}(z)
\end{aligned} \tag{6}$$

Using the definition of mathematical expectation, $E(\min(R_1, R_2))$ can be calculated using Equations 7.

$$
\begin{aligned}
E(x) &= \int_{-\infty}^{+\infty} f_X(x).x.dx => \\
E(\min(R_1, R_2) &= \int_{-\infty}^{+\infty} f_{\min(R_1,R_2)}(z).z.dz \\
&= \int_{-\infty}^{+\infty} \Big(f_{R_1}(z) + f_{R_2}(z) - f_{R_1}(z).F_{R_2}(z) \\
&\quad - f_{R_2}(z).F_{R_1}(z) \Big).z.dz \\
&= \int_{-\infty}^{+\infty} f_{R_1}(z).z.dz \\
&\quad + \int_{-\infty}^{+\infty} f_{R_2}(z).z.dz - \int_{-\infty}^{+\infty} f_{R_1}(z).F_{R_2}(z).z.dz - \int_{-\infty}^{+\infty} f_{R_2}(z).F_{R_1}(z).z.dz \\
&= \mu_{R_1} + \mu_{R_2} - \int_{-\infty}^{+\infty} f_{R_1}(z).F_{R_2}(z).z.dz - \int_{-\infty}^{+\infty} f_{R_2}(z).F_{R_1}(z).z.dz
\end{aligned}
\tag{7}
$$

The proof for more than two variables is straightforward.

3. ILLUSTRATIVE EXAMPLE

In order to describe the proposed model, consider a simple network with seven links illustrated in Figure 2. The travel time of each link is listed in Table 1.

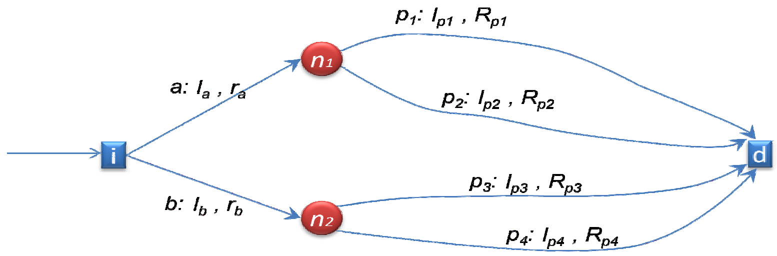


Figure 2 – A simple example network to illustrate the proposed model

Table 1 – Travel time of each link in Figure 2

Link	Real-time travel time	Travel time random variable
a	$l_a = 5$	$r_a = N(7.3, 0.6)$
b	$l_b = 5$	$r_b = N(5.2, 0.4)$
p_1	$l_{p_1} = 5$	$R_{p_1} = N(4.4, 0.7)$
p_2	$l_{p_2} = 4$	$R_{p_2} = N(4.9, 0.8)$
p_3	$l_{p_3} = 7$	$R_{p_3} = N(5.3, 0.5)$
p_4	$l_{p_4} = 3$	$R_{p_4} = N(4.3, 0.5)$

Suppose a driver is approaching node i (current decision node) and cannot decide to select between links a and b. He asks the in-vehicle navigation system, developed based on the proposed model, for help. For simplicity and without loss of generality, we assume that travel time of each link follows a normal distribution. The driver can select either of the links a or b. In the case of selecting link a with real-time travel time of l_a and travel time random variable of r_a, he then has two alternative paths to the destination, p_1 and p_2, with real-time travel time of l_{p_1} and l_{p_2} and with travel time random variable of R_{p_1} and R_{p_2}, respectively. In the case of selecting link b with real-time travel time of l_b and travel time random variable of r_b, he then has two alternative paths to the destination, p_3 and p_4 with real-time travel time of l_{p_3} and l_{p_4} and with travel time random variable of R_{p_3} and R_{p_4}, respectively. Using Equation 1 we have:

$$\text{Best Link} = \operatorname{argmin}\{5 + \mathrm{E}[\min(\mathrm{N}(4.4,0.7), \mathrm{N}(4.9,0.8))], 5 + \mathrm{E}[\min(\mathrm{N}(5.3,0.5), \mathrm{N}(4.3,0.5))]\}$$
$$= \operatorname{arcmin}\{5 + 4.17, 5 + 4.27\} = \operatorname{argmin}\{9.17, 9.27\}$$

As the cost of selecting links a and b are 9.17 and 9.27, respectively, the systems will guide the driver toward link a and the selection of other links of the path towards destination will be deferred until the arrival to that links requested by the driver.

In addition, one may adapt other strategies for route selection such as (i) using just current travel time of each link, (ii) using just mean of travel time for each link and (iii) using current travel time, for outgoing links from current decision node, and the mean of travel times for other links. Table 2 presents the results of these strategies.

Table 2 – Different possible routing strategies with real time traffic information

Path	Stategy (i)	Stategy (ii)	Stategy (iii)	Prpoposed model
$a - p_1$	5+5=10	7.3+4.4=11.7	5+4.4=9.4	5+4.17=9.17
$a - p_2$	5+4=9	7.3+4.9=12.2	5+4.9=9.9	
$b - p_1$	5+7=12	5.2+5.3=10.5	5+5.3=10.3	5+4.27=9.27
$b - p_2$	5+3=8	5.2+4.3=9.5	5+4.3=9.3	

The first strategy just uses the current travel times to calculate the overall cost of each path to the destination. Although this real time data are valid for the immediate links outgoing from the current decision node, considering this data for other links in determining the best path, violates the assumption that traffic information is time dependent. Regarding the second strategy, by using just the mean of travel times of each links, the current travel time of the immediate links outgoing from the current decision node will not be applied in the calculation of the best path which violates the assumption that the real-time travel time has to be considered. Although the third strategy uses most of the data and is more reasonable with respect to the first two strategies, this approach uses just mean of the travel times for each link and does not consider other information available in the distribution of the travel time. The proposed model in this paper considers the minimization as an statistical process by taking the expectation of the minimum of random values representing travel time and model the route planning process more accurately.

4. MODEL IMPLEMENTATION

The framework for route guidance with real time traffic information was developed as a location based service. Location-based navigation services provide decision support by

finding and visualizing the best path regarding the driver's context such as the position of the driver, current network conditions and driver's characteristics.
The designed data structure and the implementation of the system are described in sections 4.1 and 4.2.

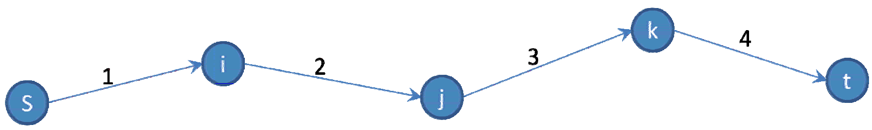
4.1. Data structure

In order to implement the model, firstly an effective data structure is required. This data structure must be able to organize the huge amount of real-time traffic information which is gathered through various sensors.
In the designed structure for each link a table is created in the database. Each row of the table allocated to one day, D_i, travel time variation of the link in which the average of travel time of that link, v_{ij}, in every t-minute interval, T_j , is calculated using the data received from the sensors and recorded as shown in Table3.

Table 3 – Organization of the real-time travel time information of each link

link a	T_1	T_2	…	T_m
D_1	v_{11}	v_{12}	…	v_{1m}
D_2	v_{21}	v_{21}	…	v_{2m}
⋮	⋮	⋮	⋮	⋮
D_n	v_{n1}	v_{n1}	…	v_{nm}

Figure 3 shows an example of a path with 3 links having traffic sensors and 1 link without sensor. The corresponding tables of each link are also included in Figure 3.



Travel time of link 1

link 1	T_1	T_2	…	T_m
D_1	v^1_{11}	v^1_{12}	…	v^1_{1m}
D_2	v^1_{21}	v^1_{22}	…	v^1_{2m}
⋮	⋮	⋮	⋮	⋮
D_n	v^1_{n1}	v^1_{n2}	…	v^1_{nm}

Travel time of link 2

link 2	T_1	T_2	…	T_m
D_1	v^2_{11}	v^2_{12}	…	v^2_{1m}
D_2	v^2_{21}	v^2_{22}	…	v^2_{2m}
⋮	⋮	⋮	⋮	⋮
D_n	v^2_{n1}	v^2_{n2}	…	v^2_{nm}

Travel time of link 3

link 3	T_1	T_2	…	T_m
D_1				
D_2				
⋮			v^3	
D_n				

Travel time of link 4

link 4	T_1	T_2	…	T_m
D_1	v^4_{11}	v^4_{12}	…	v^4_{1m}
D_2	v^4_{21}	v^4_{22}	…	v^4_{2m}
⋮	⋮	⋮	⋮	⋮
D_n	v^4_{n1}	v^4_{n2}	…	v^4_{nm}

Figure 3 – An example of a path with links having sensors as well as links without sensor and organization of their real time traffic information

4.2. System implementation and case study

To illustrate the application of the model in a real world routing problem, we use transportation network of Isfahan, a metropolitan city in the central part of Iran. The data was collected by the Isfahan Municipality in digital format at the scale of 1:2000, totalling 6,000 km of roads and 270 sq. km. of area. Figure 4 shows the relationship between different units involved in the route planning with real time traffic information.

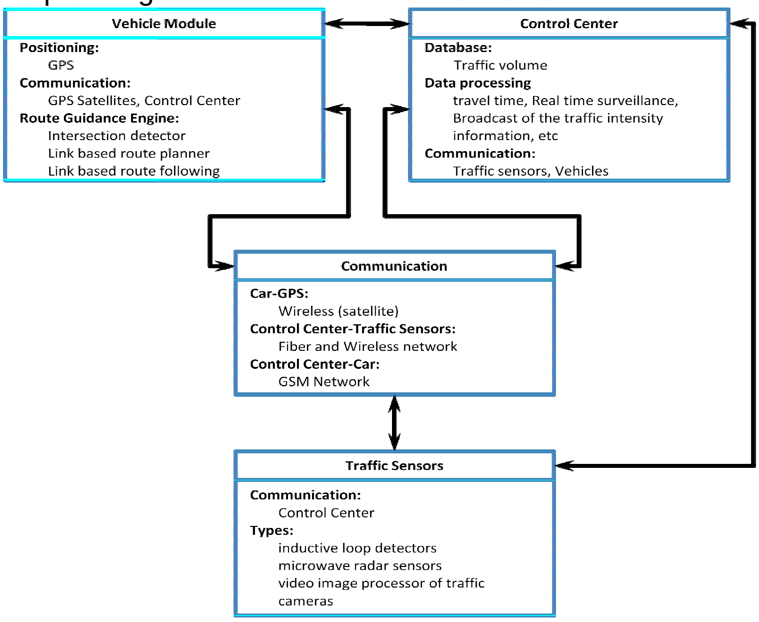


Figure 4 – Different parts involved in the route planning with real time traffic information.

The prototype was implemented using ESRI's ArcGIS Mobile, .Net compact framework 3.5 and Windows Mobile 6 Software Developer Kit (SDK). SQL Server Compact 3.5 was used for managing the collected travel time information of each link and VB.net 2008 was used as developing language.

The prototype was developed on a GPS equipped pocket PC. The processor speed and the memory resource were 400MHZ and 128MB, respectively. Figure 5 illustrates the user interface and functionalities of the implemented system.

Figure 5 – User interface of the implemented system

The driver can request navigational recommendations from system by using *Query* tool. The system requests traffic information from traffic control centre where current travel time and travel time distribution of each link is calculated and distributed as a web service. The system also determines the current position of the driver using GPS coordinates and identifies the current decision node and its outgoing links. This information is then used to determine the best link for the driver.

5. DISCUSSION

In this study, a route planning system with real-time traffic information has been successfully modelled and implemented as a location based service. The proposed model derives the best link, processing real time together with historical travel time information of links. The best link is then being recommended to the drivers using mobile GIS facilities as location based services. In a decision node (intersection), where the driver requests for navigational guidance, current travel time of outgoing links together with the distribution of travel time of other links are processed to determine the link with expected minimum travel time towards the destination. This means that if the driver follows this link and uses the system in every intersection, it is expected that he travels to the destination with minimum travel time. Furthermore, the flexible implementation of the system as a location based systems on pocket PC provides a reliable approach to address real-time on demand route guidance problem. Indeed, the model provides accurate decision aid by incorporating real time and historical travel time information of each link.
The advantages of the method are summarized in the following. First, by combining real-time and distribution of travel time, the model is able to effectively use available information about travel time and determine the path with least expected minimum travel time. Additionally, using the link-based strategy proposed in this paper; drivers can incorporate their expertises in the route planning. When the driver can select his route based on his experiences, the system does not recommend him any link but when the driver encounters some difficulties selecting between some links in an intersection, the system will provide him with the best

solution. Finally, one of the major advantages of the proposed architecture is that it helps to integrate driver's experiences, recommendations of the system and the traffic situation.
Besides the advantages of the proposed real time routing technique, there are also some areas limitations with this research that should be addressed for future assessments. First, the model deals with so many processes which its efficiency for running entirely on pocket PC device is a challenging issue. The model should be implemented as a client server tool in which some of the processes can be done on the server, and pocket PC device can just be used for visualizing results to the deriver. Furthermore, as there are route planning criteria other than the travel time such as number of stop signs, travel distance and number of turns, the model can be extended to incorporate such multiple dynamic and static criteria simultaneously.

6. CONCLUSION

This paper has proposed the theoretical basis for route planning with stochastic and time dependent real time traffic information. In this study, we take route planning with real time traffic information one step further by i) using real time traffic information integrated with its distribution for each link ii) implementing the system as a location based service on a pocket PC device and iii) introducing link based route planning techniques which let drives to incorporate their experiences in the route planning. The demonstrated approach is unique with respect to previous works on route planning as the use of a link-based strategy for routing enables users to include their practical knowledge into the process of determination of the best link.
The implemented model within a mobile-based GIS provides a framework for route planning that enhances the existing location based navigation services. Our implementation is entirely mobile based and is designed for en-route route planning. Future research is needed to investigate usability and usefulness of the system by conducting tests addressing both the user interface design and the suggested method.

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