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DRIVERS' EN-ROUTE DIVERGENCE BEHAVIOR MODELING USING EXTENDED BELIEF-DESIRE-INTENTION (E-BDI) FRAMEWORK

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ABSTRACT

The goal of this paper is to analyze drivers' en-route divergence behaviors when a road way is blocked by a car incident. The Extended Belief-Desire-Intention (E-BDI) framework is adopted in this work to mimic real drivers' uncertain en-route planning behaviors based on the drivers' perceptions and experiences. The proposed approach is implemented in Java-based E-BDI modules and DynusT® traffic simulation software, where a traffic data of Phoenix in the U.S. is used to illustrate and demonstrate the proposed approach. For validation of the proposed approach, we compare the drivers' en-route divergence patterns obtained by E-BDI en-route planning with the divergence patterns provided by Time Dependent Shortest Path (TDSP) finding algorithm of DynusT®. The results have revealed that the proposed approach allows us to better understand various divergence patterns of drivers so that a reliable traffic system considering impacts of the sudden road way blocking events can be designed.

1 INTRODUCTION

En-route planning is one of major decisions of an individual driver who searches the optimal route (e.g., the shortest route) on a road network with given pairs of the origin and destination while driving. Especially, it frequently occurs when a road way is blocked by unexpected events such as car incidents or road way constructions. This is because drivers intend to reach their destination within their expected travel time (e.g., arriving on time at work or school). Thus, the drivers' en-route divergence behaviors have been extensively studied to design a reliable traffic system which takes into account impacts of the unexpected events. Besides, an agent based traffic simulation approach has been used to predict the en-route divergence patterns of drivers under various road blocking scenarios (France and Ghorbani 2003; Maricopa Association of Governments 2013).

In the field of agent based traffic simulation, a major issue of drivers' en-route divergence behaviors is how to mimic real drivers' en-route planning behaviors. This is because impacts of congestions caused by a sudden blocking of the road are largely dependent on drivers' en-route planning behaviors. For decades, constant value based shortest route planning algorithms such as Dijkstra, A*, and time dependent shortest path (TDSP) finding are the most popular algorithms as the en-route planning algorithm (Delling et al. 2009; Chiu et al. 2010). Although those route planning algorithms can give the shortest route to a driver while driving, the algorithms have unrealistic assumptions: (1) drivers have complete information about a road network, (2) drivers are always trying to find the shortest route, and (3) once drivers have the same information about a road network, all drivers always use the same route. However, in reality, drivers are likely to have incomplete information about a road network based on their experiences and perceptions. Even though drivers have same knowledge about a road network, each individual driver may have different route plan from other drivers. This is because each individual driver has different preference on route planning, and some drivers may consider multiple attributes to select a route (e.g., minimize travel time and risk of car incidents) (Kim, Mungle, and Son 2013).

In this paper, the Extended Belief-Desire-Intention framework (Lee, Son, and Jin 2010) is adopted to overcome the limitations of the constant value based shortest route planning algorithms. Since the Extended Belief-Desire-Intention framework (E-BDI) includes probabilistic perception and reasoning algorithms based on Bayesian Belief Network (BBN), it can capture drivers' uncertain en-route planning behaviors in a great detail. Especially, BBN conducts probabilistic inference about attributes' states (e.g., states of travel time or travel time variance) whether driver has incomplete knowledge or complete knowledge about a road network.

The rest of the paper is organized as follows. Section 2 briefly describes the background of the E-BDI framework. In Section 3, the major probabilistic route planning algorithms under the E-BDI framework will be presented. Section 4 discusses the experimental results on a case study of road network in Phoenix, AZ. Finally, we conclude our research works in Section 5 with suggested future works.

2 THE E-BDI FRAMEWORK

There are several cognitive frameworks to mimic human's perception and decision making processes such as ACT-R and SOAR. Since these cognitive frameworks find a solution from subconscious knowledge given by perception of a human, they can describe the relationships between human perceptions and their decision making process in a great detail. However, those models have not been used yet to address interdependencies among multiple options (Marewski and Mehlhorn 2011; Laird 2012).

Therefore, in order to consider psychological aspect of drivers' en-route planning with the interdependencies between multiple options, we adopt the E-BDI framework which is a unified framework involving both the perception and decision making functions (Lee, Son, and Jin 2010). There are four major components in the E-BDI framework: (1) Belief module generating Beliefs from the environment, (2) Emotional module determining an agent's mode, (3) Desire module generating Desires (e.g. goals or hoping for an outcome), and (4) Decision making module creating a multi-stage plan (see Figure 1).

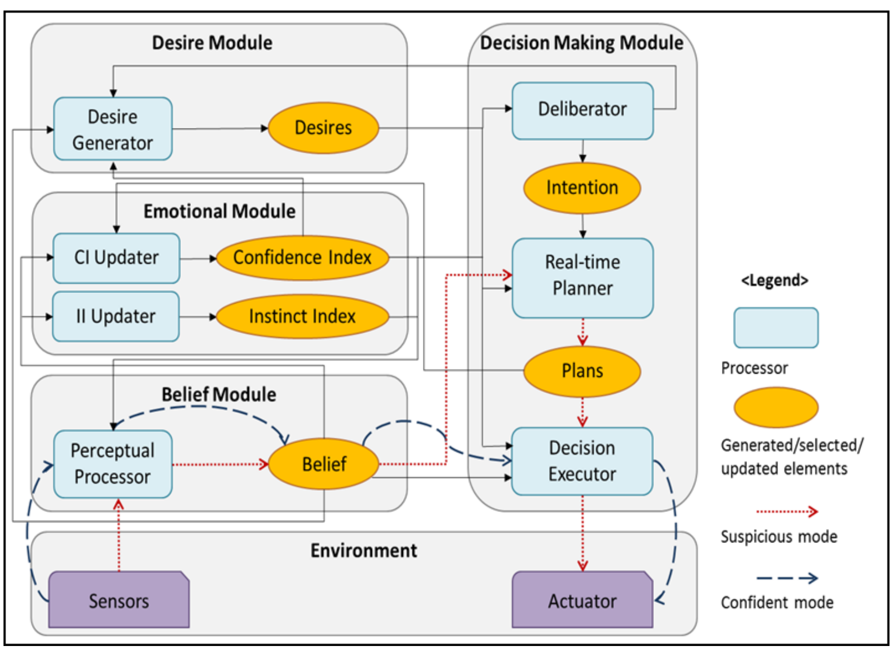


Figure 1: Components of the Extended BDI Framework (Zhao and Son 2008; Lee, Son, and Jin 2010).

At the beginning of the E-BDI framework, Beliefs are generated by Perceptual Processor in the Belief module via BBN. Figure 2 shows the BBN of drivers constructed by initial running of a simulation model (i.e., a trained BBN). In Figure 2, arcs represent interrelationship between attributes and environment variables, which is represented as conditional probabilities. Thus, the BBN infers states of attributes (i.e., Beliefs) from observed information with conditional probabilities between variables. For example, Belief of each attribute in Figure 2 (i.e., travel time or its variance) is inferred based on the states of environment variables such as free flow speed, traffic volume, and road length. If some of environment variables are unobserved, the states of unobserved variables are estimated by the trained probability distributions (e.g., low free flow speed with 57% and high free flow speed with 43%). Then, BBN generates Beliefs based on the estimated states of environment variables.

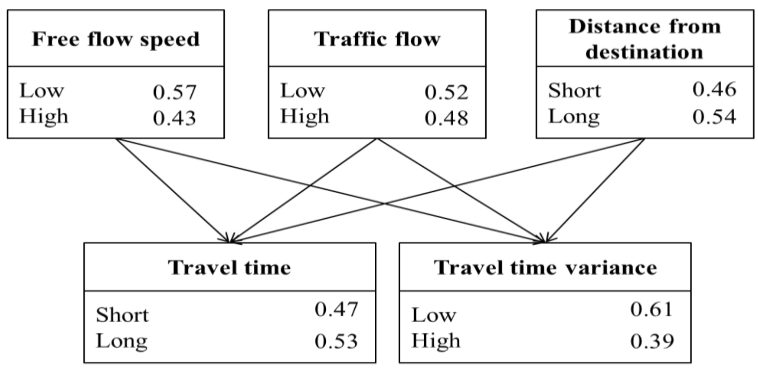


Figure 2: Bayesian Belief Network of driver agents.

Moreover, in the E-BDI framework, tasks or purpose of travel can be illustrated by Desires in Desire module, and Intention is one of Desires that an agent wants to achieve (e.g., destination) (Rao and Georgeff 1998). Once the agent has its Intention, a multi-stage plan is generated by the real-time planner in Decision making module. In order to mimic uncertain decision making behavior of a human, the Real-time planner adopts probability based planning algorithm such as Probabilistic Depth First Search (PDFS) (Lee, Son, and Jin 2010), which selects the most probable plan based on choice probabilities of multiple options (e.g., route planning with choice probabilities of a road network). The choice probabilities are calculated by the Extended Decision Field Theory (EDFT) considering interdependencies between multiple options and a dynamic evolution of preferences on the multiple options via the following formulation (Busemeyer and Diederich 2002; Lee, Son, and Jin 2008):

$$P(t+h) = S \times P(t) + C \times M(t+h) \times W(t+h) \tag{1}$$

where $P(t)$ is a preference vector including multiple options at time t (e.g., $P(t)^T = (P_1(t), P_2(t), \ldots, P_N(t))$ where N is the number of options), and the preference state is updated at every time step h. S is a stability matrix which illustrates the memory effect of previous preferences and the effect of the interactions among the options. M is value matrix to represent perceptions of a decision-maker for each option on each attribute ant its values are inferred by the Bayesian belief network (BBN). W is a weight vector to describe attention weights of a decision-maker. The matrix C is the contrast matrix comparing the weighted evaluations of each option. Once the multi-stage plan is created via EDFT and PDFS, the Decision Executor executes the plan in multi-stage (see an example in Lee, Son, and Jin 2010).

In addition, the Emotional module determines an agent's mode using the Confidence Index (CI) and the Instinct Index (II). CI is used to decide level of confidence about agent's knowledge and plan. For example, if agent has higher CI than given threshold, the framework provides previous plan without conducting planning process from the beginning. Otherwise, the framework is going through the entire decision planning and execution process that is mentioned in the previous sentences. The role of II is to illustrate spontaneous behavior of human (e.g. decisions to be made with time pressure). Thus, an agent which has high II would make a decision based on his/her long-term memory (part of Beliefs) (Lee, Son, and Jin 2010).

3 INTEGRATED SYSTEM FOR PROBABILISTIC EN-ROUTE PLANNING UNDER THE E-BDI FRAMEWORK

The proposed E-BDI based en-route planning is integrated with traffic simulation software called DynusT via web service. DynusT is a Simulation-Based Dynamic Traffic Assignment (SBDTA) software that is capable of performing mesoscopic simulation and dynamic traffic assignment for large-scale, regional networks for long time periods (Chiu et al. 2010). Although DynusT has its own framework to illustrate drivers' divergence behaviors when an incident occurs on a road, it relies on time dependent shortest path (TDSP) algorithm which generates the shortest route without considering inference and reasoning behaviors based on driver's preference. However, this limitation is resolved by the integration framework proposed in this paper as shown in Figure 3.

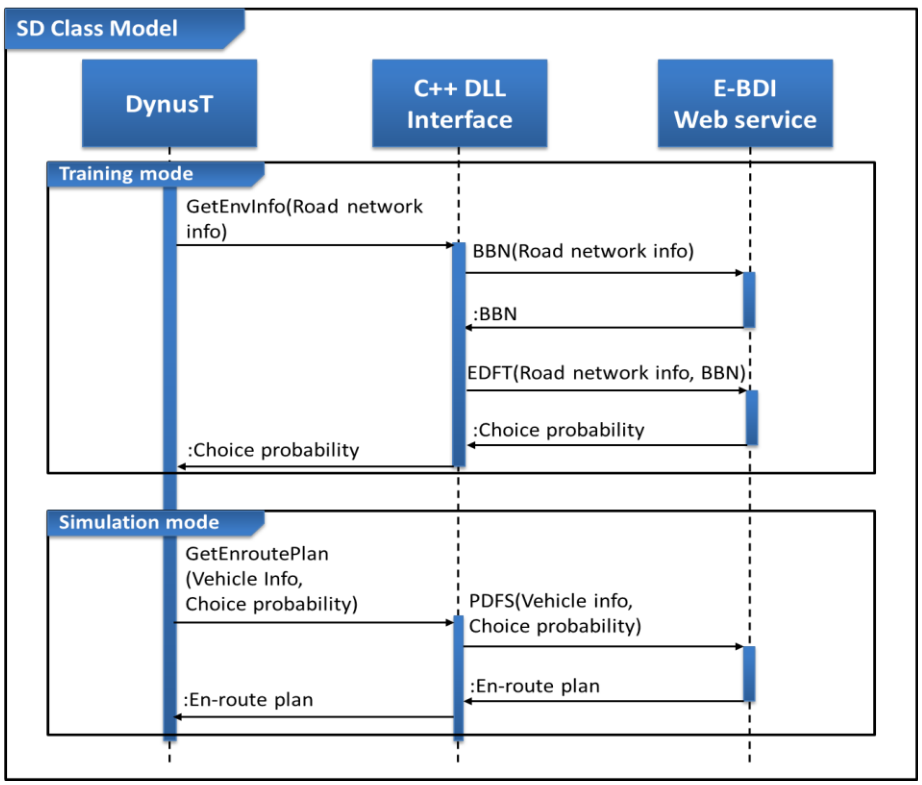


Figure 3: Sequence diagram of an integrated system for E-BDI based en-route planning.

In order to communicate between two different platforms (i.e., .DLL interface of DynusT written in C/C++ and E-BDI written in Java), web service technology is used. In Figure 3, there are two modes: (1) Training mode which generates choice probabilities for each driver type and (2) Simulation mode which conducts E-BDI based en-route planning based on the choice probabilities given by Training mode. In the Training mode, the .DLL interface of DynusT corrects observed data to construct a BBN and to calculate choice probabilities. When the E-BDI based en-route planning is triggered in DynusT, the .DLL interface records various data such as vehicle ID, observed data while driving (e.g., traffic volume and travel time), O-D pair, and vehicle type instead of conducting the en-route planning. Then, based on the collected information while simulation, BBN and choice probabilities for each driver type are calculated via E-BDI web service at the end of the Training mode. Once the BBN and choice probabilities are constructed in the Training mode, the E-BDI based en-route planning is executed during the Simulation mode. When the E-BDI based en-route planning is triggered in DynusT, the .DLL calls the E-BDI web service to generate a route based on the driver type and observations about the road environment. Then, the .DLL interface substitutes the original route plan of a driver by the new route plan given by the E-BDI web service.

By applying this two-stage approach, we can improve the computation efficiency of the integrated system since each type of drivers shares the same BBN and choice probabilities. It means that DynusT does not need to construct a BBN and choice probabilities for the same driver type when the E-BDI based en-route planning is triggered.

3.1 Interface of DynusT

In order to communicate with the extended BDI-based en-route planning model, an interface coded in C++ is compiled as a dynamic link library to be called for by DynusT. Figure 4 presents the framework of the communication between DynusT and .DLL interface.

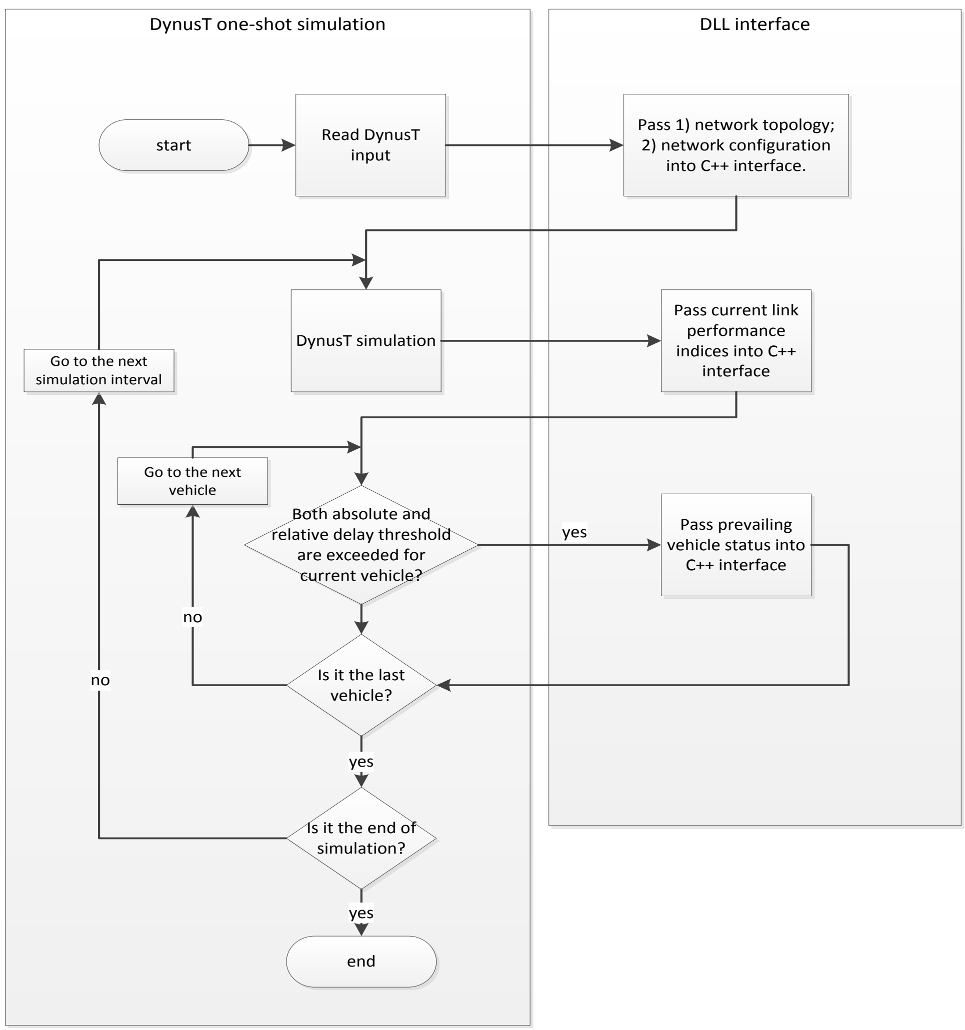


Figure 4: DynusT .DLL interface framework.

Several data such as a network topology, network configurations, real time link performance indices and real time vehicle statuses are passed from the DynusT main program into the E-BDI web service through the .DLL interface. The function to transfer vehicle status information, which depicts the current position and route of a certain vehicle, is triggered by predefined conditions. In fact, there are two time-based triggers of E-BDI based en-route planning: absolute delay threshold which is the difference between the experienced travel time and the idealized travel time exceeds a certain user defined value and relative delay threshold which is the difference between the experienced travel time and the idealized travel time exceeds a certain percentage of the idealized travel time. Whenever the prevailing experienced travel time exceeds both the absolute delay threshold and the relative delay threshold, the en-route planning behavior will be triggered and the vehicle's current status will be passed into the E-BDI web service for en-route planning.

3.2 E-BDI based En-Route Planning

In this work, Probabilistic Depth First Search (PDFS) algorithm (Lee, Son, and Jin 2010) is used to generate a route plan based on the choice probability given by EDFT and BBN method. At each node, the PDFS algorithm likely expands to a neighbor node which has the highest probability among all options. This process will continue until the algorithm reaches the destination or a given number of planning steps. Since PDFS searches for a route within the number of planning steps, PDFS considers the amount of driver's knowledge about a road network. Besides, instead of generating the optimum route (e.g., the shortest route), PDFS algorithm creates the most probable route in terms of preferences on attributes (e.g., travel time and travel time variation) based on driver's perceived information and knowledge about a road network. Thus, drivers' realistic en-route planning behaviors can be represented (Kim, Mungle, and Son 2013). Figure 5 shows the pseudo code of the PDFS algorithm.

```
1:  CALL PDFS to generate a route plan
2:    SET a current intersection v as a staring node of ROUTE PLAN S
3:    SET a planning horizon q as a zero
4:    REPEAT
5:      SET t is the latest intersection of S and ADD one to q
6:      IF t is a destination or q is equal to the given number of planning horizons THEN RETURN S
7:      CALL BBN and EDFT to calculate choice probability for all connected PATHs of t
8:      FOR the all connected PATHs
9:        IF a PATH has been selected THEN SET a choice probability as zero CONTINUE with the
          next PATH
10:       SELECT a PATH based on the probability distribution given by BBN and EDFT
11:       SET a selected PATH w as an adjacent intersection
12:       IF w is not visited
13:         SET a PATH as tree edge and w as visited
14:         ADD w to S as the latest intersection and CONTINUE at line 5
15:       ELSE
16:         SET w as back edge
17:       SET t as explored
20:       DELETE t from S
21: UNTIL S is not empty
```

Figure 5: Pseudo code of PDFS algorithm under the E-BDI framework (Lee, Son, and Jin 2010).

4 EXPERIMENTAL SCENARIO

To implement the proposed E-BDI based en-route planning approach, a real incident case on Interstate 10 (I-10), west of Phoenix, Arizona is considered. This is because the I-10 is a vital freeway corridor in the Phoenix metro region which has 11,550 nodes and 24,869 paths (Maricopa Association of Governments 2013). In fact, the traffic operation on I-10 is frequently disrupted by traffic incidents of varying severity. The heaviest disruptions are caused by events requiring full freeway closures that cause heavy traffic congestion on and off the freeway for several hours, often leading to secondary crashes and off-freeway congestion. Thus, based on the real incident data given by Maricopa Association of Governments (2013), we developed the simulation model which has a full closure incident between 35th Avenue and 83rd Avenue on I-10 east bound direction freeway. Table 1 shows the settings of this experiment, and Figure 6 reveals the snapshot of the Phoenix road network in DynusT.

Table 1: Experiment setting for the performance analysis on the Phoenix network.

Parameter		Value
Number of replications		10
Number of vehicles in network		3,102,771
Simulation time horizon		360 min.
Incident duration		120 min.
Delay threshold for the en-route planning	Absolute	Normal (10, 2) min.
	Relative	0.5

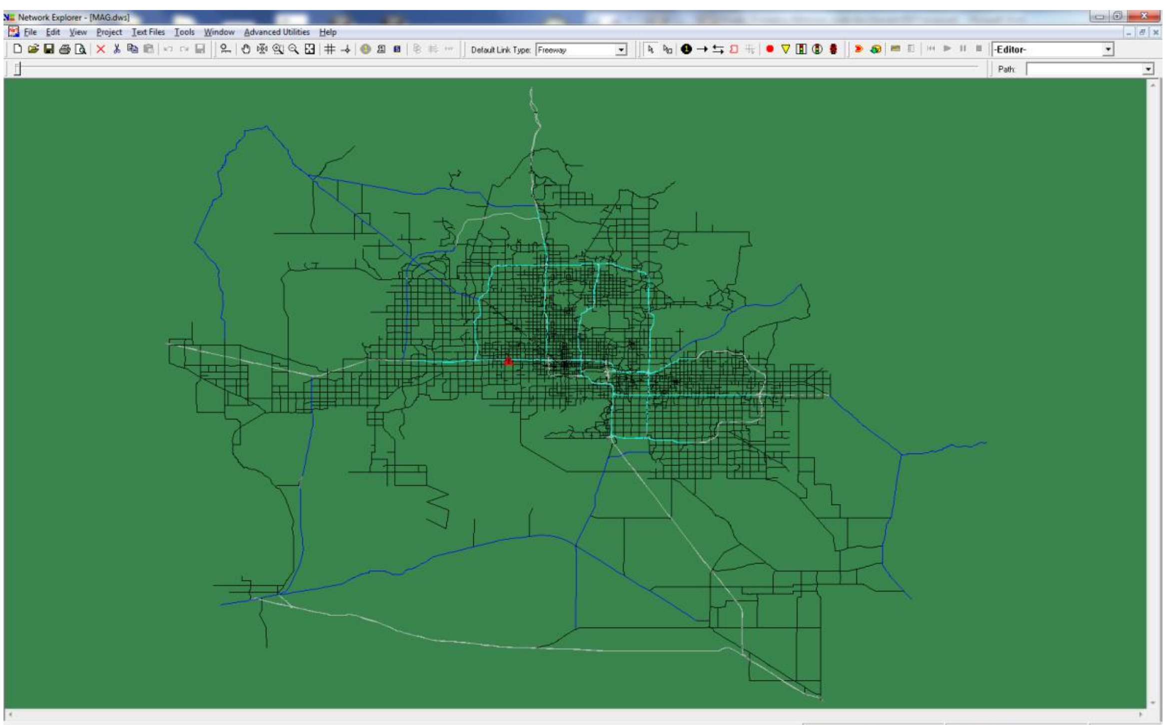
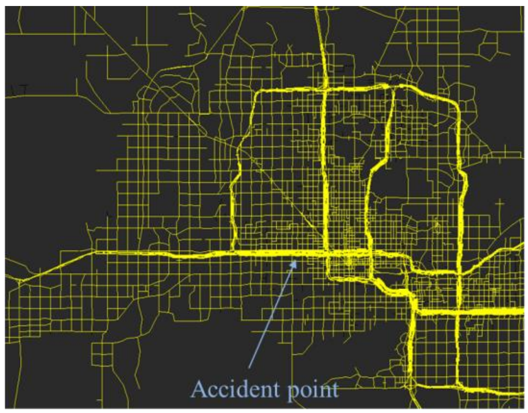


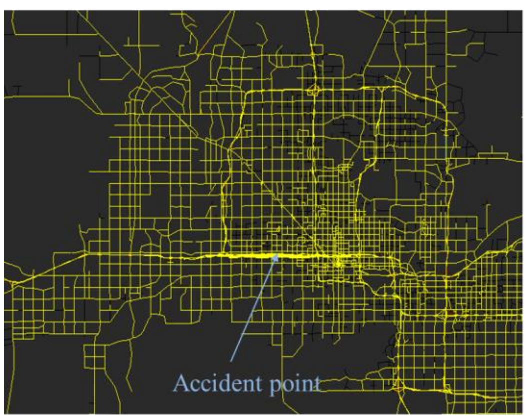
Figure 6: Snapshot of a Phoenix road network in DynusT (Incident location is marked).

4.1 En-Route Behavior in System Level

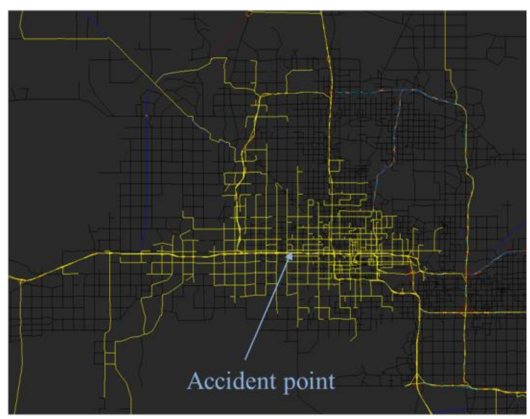
In the scenario, 43,460 (1.40% of total vehicles) vehicles pass the incident area on I-10 with 113.12 minutes (average delay time 79.23 minutes) average travel time and 25.03 miles average travel distance. As mentioned in Section 4, I-10 is a significant road way since most vehicles in Phoenix go through I-10, even though the vehicles have various O-D pairs. This means the impact of an incident could be related to all traffic situations in Phoenix, AZ. Figure 7 shows the trajectories of diverted vehicles under two conditions: (1) DynusT case with the embedded en-route planning algorithm of DynusT (i.e., TDSP algorithm) and (2) E-BDI case with the E-BDI based en-route planning algorithm. In E-BDI scenario, we consider single attribute (i.e., travel time) case and two attributes case (travel time and travel time variance with 0.5 weight value for each attribute) (see Eq. (1)).



(a) DynusT



(b) E-BDI (travel time)



(c) E-BDI (travel time and travel time variance)

Figure 7: Trajectories of diverted vehicles.

In Figure 7, the yellow line represents trajectories of diverted vehicles from their original route plans after conducting en-route planning. Most of vehicles in Figure 7(a) are likely to divert from their original plans when their current travel time information of a route is different from that of the expected travel time. All 4,052 en-route planning vehicles are diverted since the embedded en-route planning algorithm of DynusT generates a route plan based on real time information of all roads in the network (i.e., travel time). In other words, it assumes that all drivers are able to get dynamic travel time information in real time involving routes that drivers have never used and always generate the shortest route plan based on the real time information. The average travel time is 84.01 minutes (with the average delay time of 42.05 minutes) and the average travel distance is 27.96 miles.

On the other hand, E-BDI based en-route planning with a single attribute shows the less number of diverted vehicles (i.e., 87.13% of 4,052 en-route planning vehicles) than the DynusT case. This is because E-BDI en-route planning uses predicted information of a road network (e.g., travel time and travel time variance) based on BBN with drivers' own observations. It implies that a driver's route plan cannot be changed after conducting en-route planning if the driver has the same beliefs about a road network. Average travel time of E-BDI en-route planning vehicles is 92.87 minutes (average delay time 51.62 minutes) and average travel distance is 27.08 miles. In addition, E-BDI based en-route planning with two attributes shows the less number of diverted vehicles (i.e., 25.24% of 4,052 en-route planning vehicles) than any other cases. Since this case considers travel time variance as an additional attribute, drivers tend to use a route which has low travel time variance even though they need to sacrifice their travel time. In this case, average travel time is 102.45 minutes (average delay time 69.38 minutes) and average travel distance is 26.16 miles. Considering the three patterns in Figure 7, E-BDI framework reveals similar divergence pattern of drivers to DynusT model when the framework considers travel time only but it can also shows different pattern with multiple attributes and drivers' preferences on the attributes.

4.2 En-Route Behavior in Individual Level

The embedded en-route planning algorithm of DynusT is likely to show the single dominant pattern that the generated route plans have less travel time and longer distance than original route plans. This is because TDSP algorithm with dynamic information of travel time provides the shortest route plan in real time. On the other hand, E-BDI based en-route planning reveals various divergence patterns because it uses predicted information of a road network to generate a new route plan. Figure 8 shows the four major divergence patterns of an individual driver agent under the E-BDI based en-route planning with multiple attributes.

In Figure 8, the black line represents an original route plan with knowing about incident on a road, and the red line represents a new route after conducting en-route planning. In the first case shown in Figure 8(a), a driver agent changes its original route to reduce travel time. Although the new route plan has longer distance than the original route (i.e., the original route is 14.49 miles and the new route is 18.48 miles), the driver agent can save its travel time about 104.55 minutes by using the new route. Among 25.24% of 4,052 en-route planning vehicles, 23% vehicles have this pattern. Similarly, in Figure 8(b), a new route plan can reduce 71.18 minutes travel time from the original plan and 19% of diverted vehicles have this pattern. In fact, the original plan mainly uses I-10 because highway has higher free flow speed (65miles per hour) than regular road (45miles per hour). However, because of an incident on I-10, there is no benefit to use I-10 so that a driver agent uses a new route plan which has 0.06 miles shorter distance than the original route. On the other hand, Figure 8(c) and Figure 8(d) show different patterns from the previous two patterns. In both figures, drivers leave highway after passing the incident location. In fact, drivers in both figures generate route plans when they locate at incident point. 32% of diverted vehicles have the pattern in Figure 8(c) and 26% of diverted vehicles have the pattern in Figure 8(d). This means they are trapped in the accident area when they conduct en-route planning. Since E-BDI do the probabilistic route planning, it is possible that a new route has longer distance and travel time than its original route shown in Figure 8(c). The travel time gap between the new route and the original route is 3.82 minutes with 11.56 miles travel distance. In Figure 8(d), a driver agent gets out of the I-10 after it passes the incident point. Although the driver agent reduces travel distance from its own original route plan (i.e., -1.14 miles) but travel time is slightly increased (i.e., 9.11 minutes). Although the patterns of Figure 8(c) and Figure 8(d) are frequently shown in the multiple attributes case, the single attribute case of E-BDI based en-route planning reveals opposite situation (i.e., 43%, 26%, 14%, and 17%, respectively). This is because driver agents care the travel time without considering travel time variance to select a new route.

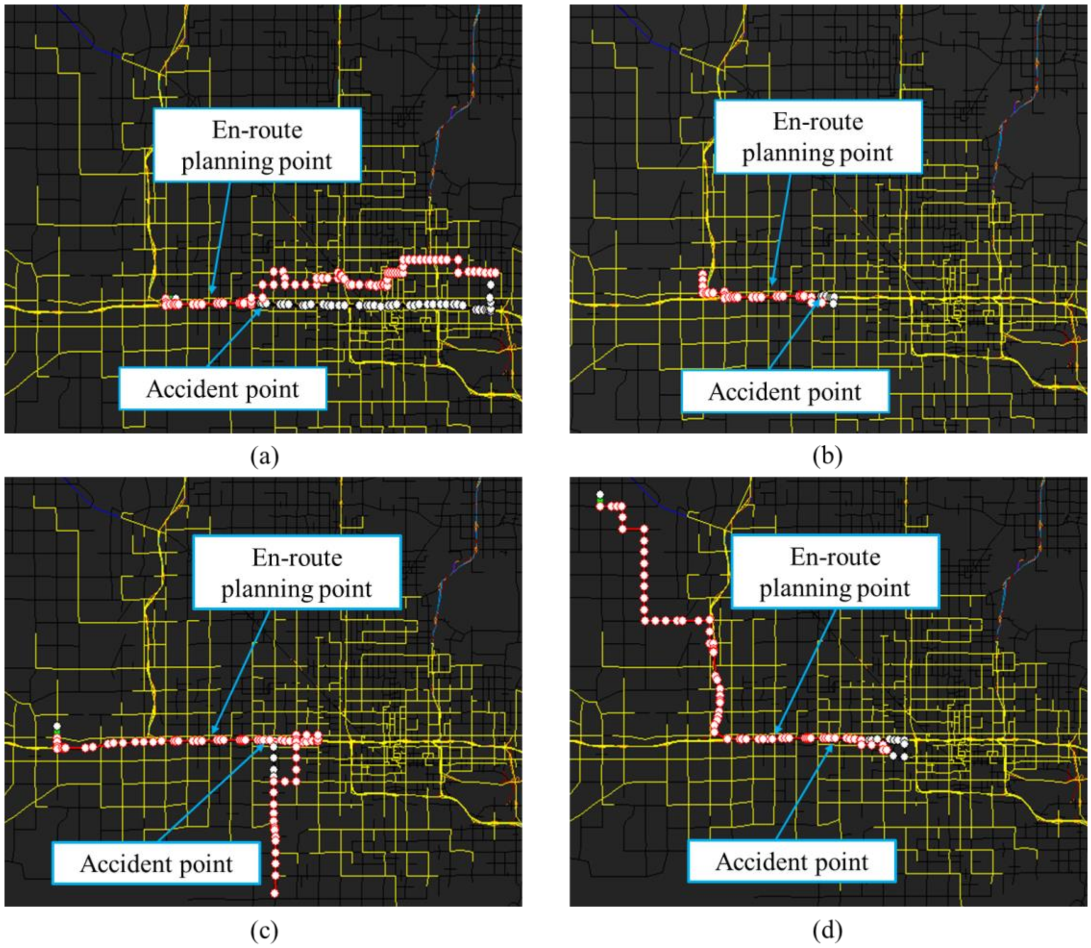


Figure 8: Divergence patterns of an individual driver.

5 CONCLUSIONS

In this paper, we proposed the E-BDI based en-route planning approach to mimic psychological aspect of real drivers' inference and reasoning processes. In order to implement the proposed E-BDI based en-route planning to mesoscopic traffic simulation software such as DynusT, an integrated system architecture involving C++ interface of DynusT and E-BDI web service has been developed. Besides, two stages approach (i.e., training stage and simulation stage) for the E-BDI based en-route planning has been proposed to construct the BBN model and choice probabilities of a road network with low computation. Therefore, driver agents in DynusT have been able to conduct the E-BDI based en-route planning regarding their own knowledge about a road network and preferences on multiple attributes. The proposed approach has been illustrated for drivers' en-route divergence behaviors based on the real incident data of Phoenix, AZ. To show the advantage of our proposed approach, we compared our results obtained from the proposed E-BDI en-route planning approach with those obtained from the embedded en-route planning of DynusT under the system level as well as the individual level. The results revealed that the proposed E-BDI en-route planning approach enables us to understand various divergence patterns of drivers with different drivers' preferences and decisions. Therefore, by considering the various divergence patterns of drivers, the proposed approach helps to design a reliable traffic system which can handle an unexpected road way such as blocking by car incidents or road way constructions more effectively.

For future works, the proposed E-BDI based en-route planning approach can be validated with real divergence pattern data of drivers. Besides, the approach can be improved by considering multiple driver types with additional attributes (e.g., road safety) to mimic real drivers' behaviors accurately. This will help control traffic so that the traffic congestion caused by car accidents will be reduced.

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