Agent-Based En-Route Diversion: Dynamic Behavioral Responses and Network Performance Represented by Macroscopic Fundamental Diagrams

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Abstract
This paper focuses on modeling agents’ en-route diversion behavior under information provision. The behavior model is estimated based on naïve Bayes rules and re-calibrated using a Bayesian approach. Stated-preference driving simulator data is employed for model estimation. Bluetooth-based field data is employed for re-calibration. Then the behavior model is integrated with a simulation-based dynamic traffic assignment model. A traffic incident scenario along with variable message signs (VMS) is designed and analyzed under the context of a real-world large-scale transportation network to demonstrate the integrated model and the impact of drivers’ dynamic en-route diversion behavior on network performance. Macroscopic Fundamental Diagram (MFD) is employed as a measurement to represent traffic dynamics. This research has quantitatively evaluated the impact of information provision and en-route diversion in a VMS case study. It proposes and demonstrates an original, complete, behaviorally sound, and cost-effective modeling framework for potential analyses and evaluations related to advanced traffic information system (ATIS) and real-time operational applications.

En-route diversion, agent-based simulation, dynamic traffic assignment, Macroscopic Fundamental Diagram

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1 Introduction

En-route diversion is a significant travel behavior that occurs frequently in every-day travel. Recurrent congestion, non-recurrent incidents, work zones, etc. are likely to trigger drivers to change route. Drivers usually make this decision based on their own spatial/temporal knowledge. They identify alternative route(s), extract and compare the likely travel conditions on both the downstream links and the alternative route(s) using their knowledge and subjective beliefs formed from prior experiences. More recently, information provision alters this situation a great deal. With technical improvement, Advanced Traffic Information System (ATIS), smart-phone applications, and GPS devices with en-route information become readily available in daily travels. Drivers can easily acquire pre-trip and/or en-route information when any diversion decisions are to be made. For instance, when traffic incidents take place in the downstream roadway segments, variable message signs (VMS) can convey real-time traffic information and encourage diversion. This arouses new research questions that need to be better addressed:

- to what extent do travelers comply to en-route information?
- how do we effectively evaluate information provision schemes and measure the network performance changes?

The authors are thus motivated to develop a useful analysis tool to accurately model en-route diversion, predict behavioral responses, and quantify the impact on transportation network. With enhanced computational power and the exploration of new paradigms, transportation modelers’ ambition to go “microscopic” and “dynamic” has never been greater. This paper proposes a comprehensive analysis tool which integrates a calibrated agent-based en-route diversion model and a simulation-based dynamic traffic assignment (DTA) model. In order to answer the aforementioned first research question, this paper focuses on microsimulating agent behavior and gauging the model parameters based on calibration and solid empirical evidence. In order to answer the second research question, the behavior model is dynamically linked with a simulation-based DTA model. This integration is completely agent-based and produces time-space trajectories for each simulated agent. Moreover, it estimates time-dependent network conditions for quantifying the network performance. In order to demonstrate the applicability of the proposed model, a case study using a subset network for Washington/Baltimore region is presented in this paper.

The remainder of the paper is organized as follows. Section 2 presents a literature review on behavior modeling and network performance measures. The integrated modeling framework of the agent-based model and operational applications is proposed in Section 3. Section 4 introduces the behavior model and calibration method. The network model and various performance measures are presented in Section 5. The integration and results are interpreted in Section 6. Conclusions and discussions on future research directions are offered at the end of the paper.
2 Literature Review

2.1 Behavior modeling

Drivers’ en-route diversion behavior has been traditionally modeled by the econometric theory of random utility maximization. In 1990s, a great deal of research efforts have been spent on this line of research. Bivariate and multinomial probit models have been used to model joint pre-trip departure time and en-route diversion behavior in response to real-time information (Khattak et al., 1995; Mahmassani and Liu, 1999). Logit models were also developed to capture the effect of information provision when drivers were en-route (Abdel-Aty et al., 1997). Stated preference and revealed preference data were typically applied to estimate these types of models. More recently, mixed logit, which can incorporate more heterogeneous taste variations, has been broadly employed in modeling diversion behavior (Ben-Elia and Shiftan, 2010; Gan and Ye, 2014). Gao et al. (2010) developed non-linear utility functions based on cumulative prospect theory (CPT) to consider the flexibility towards risk when real-time traffic information is provided. In these recent advances, information on travel time and travel time reliability on the original route and the diverting route plays a crucial role in influencing drivers behavior. Ben-Elia et al. (2013) then analyzed how different information accuracy would influence behavior.

One obvious limitation for random utility maximization models is the assumed perfect rationality. In these models, it is assumed that drivers know the probabilistic distribution of link travel time and can make a rational decision (under risk in some cases). This limitation is especially evident when modeling en-route diversion behavior, as the en-route diversion is a decision triggered by impulsion and governed by uncertainty. Rather than acquiring the real-time information, processing the information, comparing the original route with the diverting route, and reaching a decision, drivers’ knowledge is more likely to be biased and their en-route diversion is more likely to be governed by certain heuristics or rules (Paz and Peeta, 2009). Rule-based computational process models were explored by researchers to look at various behaviors including activity-scheduling (Ettema et al., 2005) and mode choice (Janssens et al., 2006). Bayes’ Rule is believed to be among the most prominent behavioral rules to represent decision-making under uncertainty (El-Gamal and Grether, 1995). In the field of travel behavior modeling, Bayes’ Rule has been employed to update model parameters (e.g. Amador et al., 2005; Janssens et al., 2006; Xiong et al., 2015). Travelers’ day-to-day perception evolution has been modeled using Bayes updating (e.g. Jha et al., 1998; Xiong and Zhang, 2013b). And there are studies using Bayes’ Rule to infer drivers’ behavior and innate emotional status (e.g. Malta et al., 2011). The application of rule-based approach in en-route diversion modeling is coarse except one research to model and recalibrate the if-then diversion rules based on fuzzy logics and weight factors (Paz and Peeta, 2009). The behavioral foundation and flexibility of the Bayesian method can be quite substantial for modeling en-route diversion before any pertinent new theories are devised to accommodate those apparent violations of perfect rationality.

From a practical point of view, another limitation of the existing behavior models is that they are often not well-calibrated due to data limitation and other issues. The
inherent bias of the stated preference data and driving simulator data have long been argued as a major deficiency of the models (Bonsall and Parry, 1991). The simulation experiment may reinforce the subject’s perception of the simulator as artificial. In practice, drivers’ route knowledge and en-route diversion propensity differ on a case-specific basis. For instance, in some cases, drivers may have strong preference to stay on the original route due to inertia. And if applying the model estimated using laboratory-collected data to analyze the diversion, one may get biased results. The information-sensitive behavioral models may be context dependent and the transferability of the diversion model may be an issue when the planning and operational applications of the model to a specific diversion scenario are of interest. Koutsopoulos et al. (1994) further asserted that driving simulators for en-route diversion analysis could be more useful if revealed preference data collected from “actual en-route route choice behavior” and an appropriated designed calibration became available.

2.2 Operations and network performance measures

Limited number of studies tried to consider en-route diversion and information provision in operational applications. Xu et al. (2011) developed a probit model by employing real-world loop detector data and vehicle plate reader data to analyze the impact of VMS. Their study emphasized the significant difference between field observations and stated preference survey responses. However, quantitative evaluation of the impact on network-level traffic conditions was lacking. Bustillos et al. (2011) embedded en-route diversion into a real-world regional network to evaluate the impact of incident scenarios. The en-route decision was modeled using a presumed delay tolerance threshold. The behavioral foundation of the model needs further empirical justification. Tsubota et al. (2013) explored the impact of en-route behavior changes under information provision by employing the Macroscopic Fundamental Diagram (MFD) as a measurement. Assumed network using microscopic traffic simulation in AIMSUN was employed to simulate different diversion ratios. These pioneer studies all seek linkages between en-route diversion and operational applications. The use of micro/mesoscopic simulators and DTA to represent traffic is helpful because the temporal/spatial variations in dynamic traffic is critical to network performance and driver behaviors. However, a complete framework that integrates en-route diversion, model calibration, network models and simulation, and performance measures is yet to be developed and is in imperative needs.

Fully taking the advantages of emerging DTA and simulation techniques, one can obtain quantitative measures to evaluate non-recurrent situations and diversion scenarios. Among various performance measures, MFD is recently widely used to evaluate the macroscopic traffic state dynamics for a two-dimensional urban road networks or freeway networks and draws our interest. The study of network-wide traffic flow relationships can be tracked back to 1960s (Smeed, 1967). Mahmassani et al. (1987, 1984) further investigated the properties of MFD using micro-simulation and real-world data. Recently, numerous and empirical and micro-simulation studies in the literature have observed the existence of a reproducible and well-defined relation between network average flow and density for urban and freeway networks (Daganzo, 2007; Geroliminis and Daganzo, 2008;
Geroliminis and Sun, 2011b). These studies link the details in individual links with the description of the congestion level of networks and its dynamics.

Geroliminis and Daganzo (2008) observed a linear relation between the total outflows (trip completion rates) and exit flows and network weighted average flow rates using a field experiment in downtown Yokohama. Keyvan-Ekbatani et al. (2012) exploited the relationship of the total traveled distance per hour and the total time spent per hour obtained from emulated loop measurements of all vehicles in an urban network. Saberi and Mahmassani (2013a) explored the effects of inhomogeneity of traffic distribution on the network between average network flow, average network density, and the standard deviation of the network density. The path-dependent hysteresis (i.e. a loop with higher flows as the density increases and lower flows as the density decreases) in the freeway networks was revealed using loop detector data. MFD could be further formulated to solve the optimal perimeter control problem for urban networks (Aboudolas and Geroliminis, 2013; Daganzo, 2007; Geroliminis et al., 2013). To obtain a small variance of link densities within a sub-network which increases the network flow for the same average density based on the spatial features of congestion, Ji and Geroliminis (2012) designed a partitioning mechanism for a large transportation network so that each sub-network had a well-defined MFD.

Geroliminis and Sun (2011a) showed that the MFD of freeway networks was hysteretic and path dependent at the aggregate level. The reasons of non-existence of well-defined MFDs for freeway networks were identified as the spatial heterogeneity in vehicle density in the onset and offset of the peak period and the synchronized occurrence of transient periods and capacity drop phenomena in the offset of congestion. Saberi and Mahmassani (2013b) characterized hysteresis and capacity drop phenomena, and quantified the size of hysteresis loops in freeway networks using loop detector data from real networks.

According to the existing MFD studies, we note that the MFD provides a time-varying relationship of space-mean flow, density and speed of an entire network. It can be used to predict the capability of a roadway system, or its behavior when applying inflow regulation or capacity drop due to incidents or infrastructure failures. The maximum capacity (i.e. maximum throughput) of the network can be retrieved from the MFD. Compared to other performance measures such as network-wide averages (e.g. vehicle hours traveled, average delay, etc.) and congestion maps, MFD can supplement measures of the characteristics of the network evolution, e.g. how much network capacity is reduced. Another merit of MFD in network performance is that it can evaluate the overall performance of multiple corridors by calculating the cumulative statistics of their roadway segments. While this is a relatively less exploited area, some seminal work studying MFD characteristics under the scheme of route choice has been observed (Haddad et al., 2013; Leclercq and Geroliminis, 2013). MFDs under different routing assumptions were analyzed in Leclercq and Geroliminis (2013). MFD values were integrated in a route choice model under the framework of cooperative traffic control (Haddad et al., 2013). As a useful measurement that captures network-level dynamics, MFDs are assessed in this paper under information provision and en-route diversion. This provides a promising extension to the existing literature on dynamic routing and operations/control and can be complementary to the MFD-related studies on route choice.
3 Agent-Based Simulation Model

The framework of modeling agents’ en-route diversion behavior under information provision is illustrated in Fig. 1.

![Figure 1: Structure of agent-based en-route diversion model](image)

Routinely, travelers form a relatively stable travel pattern and route choice, especially for their daily commute travels. A user equilibrium condition well represents this situation. When en-route traffic conditions change at time period \( t \) due to, for instance, recurrent/non-recurrent congestion, incidents, and work zones, stimuli for the agents to make en-route behavior changes, as well as the stimuli for operations strategy makers to encourage diversion, becomes more significant. Various ATIS strategies can be employed here to provide real-time traffic information. The travel conditions at time \( t \) for both the congested original route and the diverting route will be conveyed to agents during the period \( t + 1 \). While the response to ATIS can be modeled by a myriad of methods, we employ an innovative Bayesian approach to empirically model and re-calibrate the agents’ en-route diversion by using behavior data collected from the driving simulator and field observations collected by Bluetooth sensors deployed at two real-world diversion scenarios. This agent-based model predicts the diversion decision for each individual simulated in the model. Then the agent behavior is aggregated and fed back into the network traffic simulator to obtain the traffic conditions for the next time period. The use of simulation modeling allows examination of the agents’ en-route diversion under various ATIS scenarios.

4 Agents’ En-Route Diversion Behavior

The agent-based model includes these two components: (1) the Naïve Bayes model is employed to represent behavioral rules; (2) The Bayesian calibration is employed to re-calibrate the model based on local observations. This paper aims at studying these two
tools’ applicability in the context of a real-world agent-based simulation and demonstrating the superior transferability brought in by the Bayesian calibration. These two tools are explained in this section.

4.1 Naïve Bayes Model

Agents’ behavioral rules are represented by the Naïve Bayes model developed in Xiong and Zhang (2013a). This method is based on the more general Bayes’ Rule and data mining techniques, which is believed to embed more reasonable behavioral foundation without assuming random utility maximization. The study employs stated preference data collected from carefully designed driving simulator scenarios. In the experiment, subjects were required to drive slowly at the beginning of each scenario to observe a route map of the entire network. A number of diverting points were built in the network, where subjects were asked to make diversion choices. During the experiment, subjects at each diverting point were shown different travel times and time ranges for their routine route and diverting route(s) according to simulated traffic conditions. Three scenarios were assigned to each driver and each scenario was repeated six times to make sure the choices were stable. Drivers’ diversion decision has been denoted as two agent classes, being the divert class and the not-divert class. A tuple of stochastic attributes \( (F_1, F_2, \ldots, F_n) \) affects the classification variable denoted by \( C \), including travel time \( \text{Time} \) and travel time unreliability \( \text{UNR} \) of the normal route and the diverting route, travelers’ socio-demographic information (e.g. \emph{Gender}), and diverting risk \( \text{Risk} \). UNR is specified as the 95% confidence interval of the travel time duration. \emph{Risk} is a dummy variable reflecting the complexity (or risk) of the diverting route. If the diverting route involves bifurcation and possible huge delay, even if theoretically the drivers can make the correct en-route decision to avoid the delay penalty with the guidance of the real-time information at the VMS, drivers are less likely to divert. Diverting to this type of routes is considered as a diversion of high risk.

For each training observation \( F \), the naïve Bayesian classifier is a function that assigns a class label to it. This method learns the conditional probability of each variable \( F_i \) given the class \( C \). According to Bayes’ Rule, the probability of the example \( F = (F_1, F_2, \ldots, F_n) \) being not-divert class (denoted by \( C_0 \), while divert class is denoted by \( C_1 \)) is:

\[
p(C_0|F) = \frac{p(C_0)p(F|C_0)}{p(F)} \quad (1)
\]

For a training observation, naïve Bayes classifier assumes conditional independence of every other attribute given the value of the classification variable. Equation (2) shows the functional form of naïve Bayes classifier, denoted by \( f_{nb}(F) \). The empirical observation is classified as \( C_0 \) if and only if \( f_{nb}(F) \geq 1 \).

\[
f_{nb}(F) = \frac{p(C_0)p(F|C_0)}{p(C_1)p(F|C_1)} = \frac{p(C_0)}{p(C_1)} \prod_{i=1}^{n} \frac{p(F_i|C_0)}{p(F_i|C_1)} \quad (2)
\]

The estimated naïve Bayes model using the stated preference data as the full training dataset is revisited here in Table 1. These conditional priors, \( p(F_i|C_0) \) and \( p(F_i|C_0) \), can
be used to calculate the classifier (Equation 2) and thus constitute the agent behavioral rules.

Table 1: En-Route Diversion Model’s Conditional Prior Probability Estimation Results

<table>
<thead>
<tr>
<th>Classification:</th>
<th>Not Divert ($C_0$)</th>
<th>Divert ($C_1$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variables</strong></td>
<td>Conditional Priors</td>
<td>Mean (Std. Dev.)</td>
</tr>
<tr>
<td>Priors</td>
<td>$p(C_0)$</td>
<td>0.53</td>
</tr>
<tr>
<td>Gender is male</td>
<td>$p(\text{male}</td>
<td>C_0)$</td>
</tr>
<tr>
<td>Gender is female</td>
<td>$p(\text{female}</td>
<td>C_0)$</td>
</tr>
<tr>
<td>low Risk</td>
<td>$p(\text{low}</td>
<td>C_0)$</td>
</tr>
<tr>
<td>high Risk</td>
<td>$p(\text{high}</td>
<td>C_0)$</td>
</tr>
<tr>
<td>$\Delta Time$</td>
<td>$p(\Delta Time</td>
<td>C_0)$</td>
</tr>
<tr>
<td>$\Delta UNR$</td>
<td>$p(\Delta UNR</td>
<td>C_0)$</td>
</tr>
</tbody>
</table>

In the model, $\Delta$ denotes percentage changes of the attributes of alternative route from those of the routine route. The high class prior for divert class (almost as high as the class prior for not divert class) indicates that the likelihood of diversion from the routine route has been positively affected by certain factors, e.g. the provision of travel time information. Conditioned on the divert class, the probability estimates of $\Delta Time$ suggests that lower expected travel time is one major incentive that shifts individuals off their routine routes. On the other hand, the probability estimates of $\Delta Time$ conditioned on not-divert class has mean value that is close to zero and has a relatively larger standard deviation. It indicates that not-divert class is almost indifferent to expected travel time. Agents are generally risk averse, given that the estimated $p(\Delta UNR|C_0)$ is positive and greater than $p(\Delta UNR|C_1)$. Meanwhile, individuals take risk to some extent and have greater sensitivity to travel time variability since $p(\Delta UNR|C_1)$ also has positive mean. Similar risk-seeking agent behavior has been found by Ben-Elia and Shiftan (2010). The estimates on discrete variables (i.e. Gender and Risk) suggest that male drivers and drivers in lower-risk diversion situations are more likely to divert. These empirical findings conform to previous research (Khattak et al., 1993; Mannering, 1989).

4.2 Behavioral Model Calibration

From the estimated class priors (0.53 for $C_0$ v.s. 0.47 for $C_1$), one can draw the conclusion that individuals (in the driving simulator, of course) are almost indifferent between their routine route and the alternative one, given other conditions equal. However, this may be greatly different in real-world cases (Koutsopoulos et al., 1994). Drivers may react differently when actually provided with real-time information. Drivers may prefer their routines due to the inertia effect. Therefore, a recalibration process is necessary before applying the agent-based model. A separate field observation data source collected from Bluetooth detectors deployed in a real-world VMS scenario in Maryland is employed here.
Bluetooth detectors were deployed to penetrate vehicles in routine traffic flow and re-routing flow during normal traffic conditions as well as the periods whence an incident occurred. If an incident was identified, VMS in the upstream was functioning and displaying dynamic information about travel times and travel time ranges for the routine route and the alternative route. The Bluetooth detectors actively collected data for two weeks (in April 2011) and thus could penetrate sufficient vehicles that were repeatedly using the routes. For instance, if a subject who routinely used I-95 (see Fig. 3 for the location of I-95) stayed in I-95 during VMS period, her/his decision was recorded as “not divert”. Otherwise, her/his decision was recorded as “divert”. Let us denote the vector of these Bluetooth data points as $E$.

The recalibration process employed here was developed by Xiong and Zhang (2013a). It offers a mapping from the real-world behavioral data to a set of more accurate behavioral rules. By directly applying the uncalibrated naïve Bayes model to $E$, one can predict divert probabilities ranging on $[0, 1]$. If we translate the probabilities using log-odds: $s(E) = \log(p(C_0|E)) - \log(p(C_1|E))$, this measurement can range on a space $[-\infty, +\infty]$. Thus, we can model the probability density function (PDF) of the prediction score $s(E)$ (conditioned on the actually observed class) as a function of the log-odd score. This PDF $p(s|C = \{C_0, C_1\})$ is then applied as the recalibration function and plugged into Equation (3) using Bayes’ Rule and the class priors.

$$p(C_0|s) = \frac{p(C_0)p(s|C_0)}{\sum_{C = \{C_0, C_1\}} p(C) \cdot p(s|C)}$$  \hspace{1cm} (3)

More details of this Bayesian calibration method is given in Xiong and Zhang (2013a). Applying this method to analyze the actual observations $E$, we can correct the dramatically higher diversion propensity predicted by the uncalibrated model and match the predictions to the low diversion rate. In Fig. 2a we show the reliability diagram estimated for the en-route diversion calibration dataset. The x-axis shows the predicted probability of the naïve Bayesian classifier for the divert class. The y-axis shows the empirically observed relative frequency of the divert class. If the classifier is well-calibrated, all points should coincide with the diagonal line, which indicates that the predicted diverting probability are equal to the empirical probability. The model’s prediction is too optimistic, predicting diversion probabilities that are too close to 1. In actuality, the diversion percentage is much lower than the estimated value. After performing the calibration, the reliability diagram is illustrated in Fig. 2b. The Bayesian calibration successfully readjusts the model prediction to match the low diversion rate observed by the Bluetooth detectors. As shown in Fig. 2b, most of the predicted probabilities are in line with the observed relative frequencies.

This section has revisited the Naïve Bayes model of en-route diversion and its Bayesian calibration approach. These tools are then applied to predict agent behavior based on empirical observations collected from real-world Bluetooth sensors. The behavioral model departs from the utility-based models in the way that it employs Naïve Bayes rules to predict behavior. The calibration approach is a practical and powerful tool to take the advantage of any types of real-world diversion data. Data sources that are as aggregate as diversion rates or as microscopic as individual-level Bluetooth/GPS/Smartphone data...
can provide useful prior information for this approach to produce more accurate posterior probabilities. This approach is a consistent and theoretically sound parametric method to model agents’ en-route diversion behavior. It is flexible and thus can be easily transferred to other study areas to analyze diversion-related operations and management strategies, such as ATIS, VMS, the provision of real-time information, etc. It has the practical value that researchers and practitioners may potentially apply the en-route diversion model to other regions based on recalibration using locally collected field observations. This unique advantage is demonstrated in this paper through the construction of an integrated agent-based simulation model to analyze scenarios on I-95 corridor. The traffic simulator, network performance measures, and the modeling outcomes are presented in the following sections.

5 Simulation Model and Network Performance

5.1 Simulation study description

A case study is conducted on an extraction of the Metropolitan Washington Council of Government (MWCOG) network. A mesoscopic traffic simulation model for the study area is developed (Fig. 3) using DynusT package (DYNamic Urban Systems in Transportation, Chiu et al., 2010). The network includes around 2000 links, 500 nodes, over 300 signalized intersections, 201 TAZs, three major freeway corridors, and one tolling highway. As one of the latest DTA analysis tool, DynusT is chosen as the simulator. It simulates individual vehicle’s movement based on a mesoscopic traffic simulation model, Anisotropic Mesoscopic Simulation (AMS), which reveals its agent-based nature.
Three scenarios are simulated in this analysis:

- The **basecase** scenario represents the original demand pattern and dynamic user equilibrium (DUE) condition, which is calibrated using MWCOG demand model’s extended morning peak (5:00 a.m. to 10:00 a.m.) origin-destination (OD) demand as the base matrices. The total number of agents during the 5 hours of simulation is 625,389. Real-world signal timing plans, probe-vehicle collected corridor travel time data, and over 60 traffic count stations are employed as calibration evidence. The calibration is documented in Zhang et al. (2012) and Xiong et al. (2015).

- The **incident** scenario assumes an incident occurring at 5:30 a.m. and last until 6:30 a.m. on a major commuting corridor, I-95 South Bound (SB). Incident location is marked by the triangle on I-95 in Fig. 3. A closure of two lanes on the affected link is assumed in the incident scenario. Real-time information is not provided to agents (agents take their habitual routes identified in the basecase).

- The **diversion** scenario. Four VMS devices (denoted by the four blue rectangles along the freeway corridor in Fig. 3) deployed on the upstream links are assumed to be responsive to the incident. Incident message, travel time and travel time range on I-95, and the corresponding travel condition on the alternative corridor (US-29) are displayed to agents. Rule-based agents learn the prior information from the DUE iterations in the basecase scenario and make en-route decisions according to...
the naïve Bayes rules. The VMS devices are assumed to be active between 5:30 a.m. and 7:30 a.m. (one hour after the clearance of the incident). Real-time information is updated during each predefined time period (10 minutes in this case study).

An example VMS plate is illustrated in Fig 4. During each time period when the VMS devices are active, the travel conditions of the previous time period on the routine route and the alternative route are provided to agents for them to make an en-route diversion decision.

![INCIENT AT EXIT 35](image)
**Figure 4:** An example of traffic information displayed on VMS plates

In these simulation scenarios, real-time information is updated in each time period based on time-varying link travel time retrieved from the AMS model (Chiu et al., 2010). AMS is a vehicle-based mesoscopic traffic simulation approach that explicitly considers the anisotropic property of traffic flow into the vehicle state updated at each simulation period. In Section 5, the incident scenario without real-time information provision and the incident scenario considering en-route diversion under ATIS are quantitatively compared using various performance measures. In particular, MFD, defined in Section 5.2, is employed to investigate the before-and-after performance of the I-95 SB corridor.

### 5.2 Network performance: macroscopic fundamental diagram (MFD)

MFD can potentially be an intuitive and quantitative performance measure for analyzing the three scenarios. To implement the macroscopic traffic analysis on the corridor level, we may investigate the relationship of the accumulation of vehicles in a network with the exit outflows, and the equivalent relationship of the network-wide weighted average density and flow rate.

We have:

\[ N_t = \sum_{a \in A} k_{a,t} l_a \lambda_a \]  

where \( N_t \) is the time varying number of vehicles in a network denoted by \( A \), each individual link is \( a \in A \); \( k_{a,t} \) denotes the traffic density of link \( a \) at time \( t \); \( l_a \) and \( \lambda_a \) denote the length and the number of lanes of link \( a \).
\[ K_t = \frac{N_t}{L} = \frac{\sum_{a \in A} k_{a,t} l_a \lambda_a}{\sum_{a \in A} l_a \lambda_a} \]  

(5)

where \( K_t \) is the space mean density (vehicle per mile per lane) at time \( t \), \( L \) is the total length (lane-miles) of the network. Analogously, we have Eq. (7).

\[ Q_t = \frac{\sum_{a \in A} q_{a,t} l_a \lambda_a}{\sum_{a \in A} l_a \lambda_a} \]  

(6)

where \( Q_t \) is the space mean flow rate (vehicle per hour per lane) of the network, \( q_{a,t} \) is the traffic flow rate of link \( a \) at time \( t \). Both empirical observations (Geroliminis and Daganzo, 2008) and dynamic traffic assignment experiments on a real large-scale urban network (Mahmassani et al., 2013) concluded that \( Q_t \) was robust linear with the trip completion rate that was the sum of finished and exiting trips for the whole network. The network-wide weighted average speed is given by:

\[ V_t = \frac{\sum_{a \in A} v_{a,t} k_{a,t} l_a \lambda_a}{\sum_{a \in A} k_{a,t} l_a \lambda_a} \]  

(7)

where the weighted quantity is the number of vehicles on an arbitrary link \( a \) at time \( t \).

According to the traffic variables relationship in the MFD, as well as Equations (4–7), the network average speed is estimated by:

\[ V_t = \frac{Q_t}{K_t} \]  

(8)

The spatial standard deviation of densities in the network and their coefficient of variation (CV) are formulated using Eq. (9a) and (9b). CV represents the spatial distribution of link densities, which can be employed as a reliability measure and infers network flow.

\[ \sigma_t = \sqrt{\frac{\sum_{a \in A} l_a \lambda_a (k_{a,t} - K_t)^2}{\sum_{a \in A} l_a \lambda_a}} \]  

(9a)

\[ CV_t = \frac{\sigma_t}{K_t} = \sqrt{\frac{\sum_{a \in A} l_a \lambda_a (\frac{k_{a,t}}{K_t} - 1)^2}{\sum_{a \in A} l_a \lambda_a}} \]  

(9b)

These measures together form four different types of MFD and will be computed using simulated agents in Section 5. They are: (1) weighted density – weighted average flow; (2) vehicle accumulation – vehicle outputs; (3) weighted density – weighted average speed; (4) weighted density – CV of link densities.

6 Integrated Agent-Based Simulation and Results

In this section, the integrated agent-based simulation is performed. We first demonstrate the computational performance of the integrated model. Fig. 5 illustrates the run time under different configurations in terms of (1) total number of simulated agents (from 20%
of the original demand to 200%); (2) time intervals to update VMS information (from 5 minutes to 60 minutes). On a desktop with Intel i-7 2.5 GHz CPU and 8 GB RAM, five replications are simulated to ensure the stability of the results. The simulation data with their mean and error range are plotted. Although simulation runs with increased demand and fine-grained time intervals inevitably require more run time, the computational efficiency remains in a reasonable range, which clearly shows the applicability of the model.

![Graphs showing computational time for different numbers of simulated agents and different VMS time intervals](image)

Figure 5: Computational times of different configurations of the agent-based model

### 6.1 Agent-based en-route diversion responses

In this section, the empirically estimated and calibrated en-route diversion model is integrated with DynusT network model and MFD post-processing analysis. Agents’ diversion behavior response to the assumed incident and VMS scenario is analyzed and simulated. In order to reflect the dynamic nature of this operational applications while retaining the simulation in a manageable computational time, the time period length is set to be 10 minutes. Ten replications for each scenario are simulated in order to verify the stability of the results. This setup can be fine-grained whence there is an enhanced computational capability. Agent decisions are dynamically determined and provided to the DynusT model wherein the diversion scenario is simulated. Fig. 6 illustrates the agent-based simulation results.

Fig. 6 illustrates, by VMS locations, the integration results of the time-varying travel time (the bar charts) and travel time range (error bars) on the normal route and the diverting route, as well as the agents’ aggregated diversion percentage for each time period and each VMS. The darker curve represents the percentage of upstream I-95 users who have taken the off-ramps at each VMS location during basecase scenario, while the lighter curve represents that diversion percentage during diversion scenario. The VMS devices are active between 5:30 a.m. and 7:30 a.m. to provide real-time information. The results
indicate that the integrated model well captures the agents’ behavior response dynamically and at different upstream diverting points. At the very beginning of the incident (around 5:30 a.m. to 6 a.m.), the traffic condition of the corridor is close to free-flow condition and the incident does not cause too much congestion. The diversion response is minor. During the peak-of-the-peak (starting from 6:30 a.m.), severe congestion can be observed and more drivers decide to divert. For instance, nearly 15% of agents divert at VMS 1 between 6:30 a.m. and 7 a.m. in response to the higher congestion on the normal route (I-95 SB).

(a) Agent diversion at VMS 1 (the northmost)

(b) Agent diversion at VMS 2

(c) Agent diversion at VMS 3

(d) Agent diversion at VMS 4

Figure 6: Travel time and travel time variance for normal route and diverting route and the agents’ diversion percentages for the Basecase and the Divert Scenarios

Overall, the model predicted diversion percentages are moderate (the highest diversion percentage is lower than 15%; the average diversion percentage is 5.2%) and are consistent
with Bluetooth observations. And the percentages are highly fluctuating, since the road traffic evolves dynamically and a higher diversion percentage during a certain period is likely to improve the traffic condition on the route and thereby results in a relatively lower diversion percentage for the next time period. It is worth noting that the travel time reliability also plays an important role in en-route diversion, since VMS typically displays travel time range. If the diverting route’s travel time is more uncertain, risk-averse agents are less likely to divert and the integrated model yields a lower diversion percentage.

6.2 Network performance results

On the network level, the proposed model predicts that over all simulated agents, the average travel time per trip increases from 16.31 minutes in the basecase scenario to 17.83 minutes (8.1% increase) in the incident scenario. The provision of real-time information and en-route diversion can effectively mitigate the network-wide average travel time to 17.07 minutes. Simulation results for the three scenarios, including total vehicle hours traveled (VHT), vehicle miles traveled (VMT), average travel time/delay, and average travel distance, can be found in Table 2. Spatial/temporal performance measures for the I-95/US-29 corridor, including congestion maps for the directly affected I-95 SB and macroscopic fundamental diagrams for the corridor sub-network, are presented in the following subsections.

Table 2: Simulation Results for the Three Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Demand (vehicle)</th>
<th>VHT (hour)</th>
<th>Avg. Travel Time (min./veh.)</th>
<th>Avg. Delay (min./veh.)</th>
<th>VMT (mile)</th>
<th>Avg. Trip Distance (mile/veh.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basecase</td>
<td>625,389</td>
<td>169,983</td>
<td>16.31</td>
<td>3.70</td>
<td>4,605,512</td>
<td>7.36</td>
</tr>
<tr>
<td>Incident</td>
<td>625,389</td>
<td>185,864</td>
<td>17.83</td>
<td>4.59</td>
<td>4,466,686</td>
<td>7.14</td>
</tr>
<tr>
<td>Diversion</td>
<td>625,389</td>
<td>177,889</td>
<td>17.07</td>
<td>3.85</td>
<td>4,576,050</td>
<td>7.32</td>
</tr>
</tbody>
</table>

6.2.1 Congestion Maps

Fig. 7 shows the congestion maps using average speeds across all lanes of I-95 SB for each 1-minute interval in the time-distance plot. The warmer shades indicate lower speeds and more congested traffic flows, while the cooler shades represent higher speeds and free-flow states.

Fig. 7a shows the southbound traffic flow evolutions on a 13.6-mile highway segment wherein the four VMS are implemented (see the detailed layout in Fig. 3). The period analyzed is the morning peak hours under the baseline scenario. The segment of mileposts 8.0 mile through 9.5 mile formed a traffic bottleneck that triggered a heavy congestion at around 7 a.m. The traffic jam propagated upstream to the location of 5.0 mile. Till 9:15 a.m., the downstream queues began to dissipate and subsequently regained the free flow speed. It is worthwhile to point out that a local congestion state was formed at the location of 7.5 mile and continued to the end the simulation time. This was caused
by an increasing on-ramp demands merging into the I-95 SB mainline. Fig. 7b shows the mainline heavy congestion caused by the downstream incident that lasted from 5:30 a.m. through 8:30 a.m.. In the scenario without any en-route information provision, the incident occurring in the 8.0–9.5-mile bottleneck has reduced the highway capacity and induced a spill-over congestion propagating to the most upstream of the freeway segment. Distinguishing with the baseline scenario, the incident induced jam queue propagated backwards in a faster speed indicated by the larger slope during 6 a.m. through 6:45 a.m. from the mileposts 8.0 mile to 3.5 mile. It was also found that the speeds suddenly dropped from the approximate free-flow speed of 55 mph to the oscillating speed between 5 mph and 20 mph at the beginning of the incident occurrence. Though the congestion dissipated at around 9:30 a.m. in the bottleneck, a two-mile length of congested queue was still present at the end of the simulation, i.e. 10 a.m. The spatial impact length of the incident was larger than 9.5 miles in the study corridor, and the duration of congested states was as long as 4 hours.

Figure 7: Comparison of congestion maps for I-95 SB
Fig. 7c shows the effect of the en-route diversion scenario on the congestion mitigation. Diversion effectively reduced the incident-induced delays. Both the spatial and temporal impacts of the incident were significantly decreased by the en-route diversion and information provision. Compared with Fig. 7b, the spatial impact length of the incident was 6.0 miles in the study corridor, and the duration of congested states was 3 hours. In addition, drivers’ diversion behaviors also smoothed the transition from the free-flow state to the congested state for the segment of 3.5 mile through 8.0 mile. The speed breakdowns were relieved and the jam propagation was slowed down, e.g., the propagating time period was from 7 AM to 8 AM which is longer than 45 minutes shown in Fig. 7b.

6.2.2 Macroscopic fundamental diagrams

The MFDs represent the dynamic development of traffic conditions (Geroliminis and Daganzo, 2008; Geroliminis and Sun, 2011a,b; Saberi and Mahmassani, 2013a,b). In a transportation network, if traffic is distributed heterogeneously, characteristics with regard to the hysteresis and capacity drop could be observed. In this study, we analyze the 1-minute interval MFDs for the subnetwork of I-95 and US-29 using simulation, as shown in Fig. 8.
Fig. 8a depicts the relationship between the space mean flow rate and the space mean density. It can be seen that the MFD curves of three scenarios satisfy homogeneity conditions and exhibit smooth curves when the weighed density is low. When the density reaches 24 veh/mile/lane, throughput drop caused by the incident can be observed in both the incident scenario and the diversion scenario. These two scenarios thereby reach their maximum flow rates under the circumstances of higher densities. Compared to the agents in the incident scenario, those in the diversion scenario have access to en-route information and thus can better utilize the remaining capacity of the network. Hence a higher throughput is achieved in the diversion scenario. The hysteresis phenomenon (higher flows as the density increases and lower flows as the density decreases) is remarkable in each scenario, indicating that the flow rate is lower during the recovery period compared to the loading period. An interesting finding is that when agents possess en-route information, the hysteresis effect is less dramatic (in other words, the loading curve and the recovery are closer). The MFD hysteresis patterns conform to existing studies on arterial and freeway networks (Geroliminis and Sun, 2011a; Saberi and Mahmassani, 2013a; Tsubota et al., 2013). We can also observe that the densities are successfully reduced when information is available after the incident.

Fig. 8b depicts the relationship between vehicle accumulation (i.e. the number of vehicles remaining in the network at each time period) and outputs (i.e. the hourly rate of exiting flows from the network, including all off-ramp flows and the mainline flow of the ending links). Analogously, the performance of the diversion scenario lies between the basecase and the incident scenario. Fig. 8c shows the speed-based MFD curves. The network-wide average speeds are consistent and closely predicted. The diversion benefits the network by maintaining a higher level-of-service during the incident and lower densities after the incident. Finally, network reliability is measured by spatial distribution of link densities, i.e. Coefficient of Variation (CV, as defined in Eq. 9b). As illustrated in Fig. 8d, the network CV indicates that the incident, no matter with or without information provision, will result in a much more unreliable and spatially unevenly distributed traffic condition. Omitting the initial demand loading period (which leads to unevenly distributed traffic), the highest CV in the two scenarios can reach 1.5 and 1.3 in the incident and the diversion scenario, respectively. The CV gradually reaches its maximum value in the incident scenario. In the diversion scenario, a peak CV occurs at the beginning of the incident and maintains on a stable level. In other words, some additional queuing and congestion are inevitably induced as soon as agents are diverted and start to concentrate in disperse places. This is an important measure of time-varying reliability for analyzing the impact of incident and diversion and should be accounted for in any evaluation.

Notably, the MFDs of the basecase and diversion scenarios exhibit consistent patterns during the recovery, maintaining similar critical weighted average density (as shown in Fig. 8a). This is due to the topological and control characteristics of the network such that agents can promptly divert to the alternative route via multiple diverting points and the alternative route has unused capacity, few signals and limited access. Would the MFD patterns persist if these characteristics differ? We use simulation studies to shed some light on the answer and reserve more thorough analysis for future research. Two circumstances are demonstrated, including: (1) in the diversion scenario, the capacity of the alternative
route is reduced by 20%; (2) in the diversion scenario, only VMS 3 and 4 are used to divert agents. Other simulation settings remain the same. MFDs of density-flow relationship for the two cases are illustrated in Fig. 9a and Fig. 9b, respectively.

Figure 9: MFD of density-flow relationship when (a) the capacity of the alternative route is reduced by 20% in the diversion scenario; (b) only VMS 3 and 4 are enabled in the diversion scenario.

Compared to MFD of the originally assumed diversion scenario, the diversion curves in these two cases exhibit inconsistent MFD patterns. This discrepancy is most significant during congestion offset in Fig. 9a (where a significant hysteresis is observed) and during congestion onset in Fig. 9b (where lower throughput is observed). It indicates that diversion could have less effect on traffic recovery, when the alternative route has less capacity to serve diverting vehicles. And similarly, less benefit can be expected for traffic loading period if the original route has fewer diverting points.

Analogous to the dissimilarity between freeway networks with hysteresis phenomena and arterial networks without hysteresis (Geroliminis and Sun, 2011a), diversion scenarios with different topological and control attributes can lead to significantly different MFD results. Circumstances can be generalized into fourfold: (1) the network has less redundant capacity; (2) topologically, the network has fewer access points to the alternative route; (3) traffic conditions between routes are highly correlated (e.g. diversion under severe-weather situation); (4) on the demand side, the diversion has a very low compliance rate. If any of these circumstances holds, the subnetwork may have significantly different MFD patterns. It may not even have well-defined MFDs to describe a clear flow-density relationship (Geroliminis and Sun, 2011a). While this paper represents one specific case of network-level MFDs, a future study should deeply investigate and summarize MFD performance under various circumstances.
7 Closing Remarks

The objective of this paper has been to study the en-route diversion responses of agents under real-time information provision and to quantitatively analyze their impacts on network performance. In order to achieve this objective, an integrated agent-based simulation approach is proposed. On the demand side, a naïve Bayes classifier is developed to model the decision-making. Stated preference samples collected from driving simulator scenarios have been employed in the model estimation. Bluetooth-based field observations have been employed in the model re-calibration. On the supply side, this integration has incorporated a real-world large-scale mesoscopic traffic simulation model coupled with simulation-based DTA to reveal interesting traffic dynamics.

The first contribution of this paper lies in the originality and completeness of the integrated modeling framework. The rule-based behavior model serves as an plausible alternative to the traditional discrete choice models. Individuals that are perfectly rational are replaced by Bayesian agents. Moreover, the rule-based model predicts agent behavior probabilities in a highly efficient way, which especially useful when millions of agents are simulated in the system. Secondly, the model's operational application also represents a first attempt to link agent behavior with large-scale network simulation. It has demonstrated superior transferability of the agent-based model since less than five new parameters are re-calibrated and the model predicts consistent diversion behavior which matches the Bluetooth observations. The proposed framework is comprehensive. It models the agent behavior, calibrates the model, simulates network conditions, dynamically applies the behavior model, deploys the diversion strategy in the simulation, and obtains various performance measures.

This paper also remains as a first research effort that uses MFD measurements to quantitatively evaluate the information provision and en-route diversion in an assumed incident scenario. Unlike typical averaged statistics, MFD measurements are time-dependent representations of traffic characteristics. The MFDs of the studied I-95/US-29 network have confirmed that agents’ en-route diversion has an impact on network throughput, average flow, speed, and density. Compared to the incident scenario, the diversion scenario indicates a more robust network which has less significant flow decrease and recovers with weaker hysteresis. This is an important finding. Without real-time information provision, an incident has the potential to make the network much more vulnerable and suffering from severe breakdown. En-route diversion can help avoid the breakdown and maintain a consistent traffic pattern to the normal traffic pattern of the network. Another interesting finding regarding the corridor-level MFD is that according to the CV measure of link densities, some unevenly distributed local congestion is inevitable even if the overall weighted average density can be well controlled. This finding suggests that when evaluating VMS and diversion, the spatial distribution of link densities should be carefully accounted as a measurement of reliability. Finally, it is worth noting that the simulation results are case-specific and sensitive to the network topology. Diversion can be less beneficial if the behavioral compliance rate is low, or if the network does not have an alternative route as effective, e.g. the network is non-redundant or has fewer access points to the alternative route. Another situation is that the traffic conditions between routes are highly correlated.
An extreme case can be the severe-weather situation where the capacities of both routes are deteriorated. In order to fully evaluate VMS and diversion, a future study needs to systematically examine situations under various uncertainty and network scenarios.

As demonstrated in this paper, the en-route diversion model is easy to be estimated and applied in computational processes and agent-based simulation. This model is highly transferable if applying the proposed calibration functions to any available ground truth data. The proposed framework is comprehensive and can be applied in operational analysis (e.g. to evaluate ATIS strategies) and demand models (e.g. to predict more realistic en-route diversion behavior). This approach meets the imperative needs in modeling en-route diversion and real-time information provision in demand modeling and operational applications, especially when most commuting corridors in contemporary metropolitan areas get increasingly congested and ATIS, such as VMS, becomes readily available.

Despite the promising applicability of the proposed modeling framework, it is acknowledged that much needs to be done theoretically to further extend existing understanding on behavior under information provision and on MFD characteristics. MFD performances under various uncertainty, control, and topological circumstances need to be investigated in order to comprehensively assess the effect of information provision. On agent behavior modeling, laboratory experiments have shown evidences that drivers can learn from their prior experiences over time through a reinforced learning process (Ben-Elia and Shiftan, 2010; Lu et al., 2011). And the discrepancy between the information and the actual experience can influence agent learning and decision-making (Ben-Elia et al., 2013; Gao and Huang, 2012). Behavioral parameters for learning processes have been calibrated using surveys, experiments, and network simulation (Lu et al., 2014; Xiong et al., 2015). Following this line, more research is needed for modeling transportation as a complex system that accounts for the combined effect of travel information, agent behavior, and network dynamics. Another pitfall is that the framework only considers en-route behavior changes, while other dimensions of behavior adjustments are not included. In reality, ATIS and reliable traffic information could also encourage mode shifts, pre-trip route changes and trip rescheduling (Sun et al., 2012), which should be included in a cohesive multidimensional framework. Optimal ATIS strategies can be explored using the framework such as optimal VMS deployment (e.g. how many VMS devices, VMS locations, and durations) and information penetration (e.g. percentage of agents possessing pre-trip/en-route information). Simulation-based optimization and meta models can be a powerful optimizer for solving these types of decision-making problems (Chen et al., 2014).

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Reference


