On the Impact of Human Driver Behavior on Intelligent Transportation Systems

Falko Dressler and Christoph Sommer
Computer Networks and Communication Systems
Dept. of Computer Sciences, University of Erlangen, Germany
{dressler,christoph.sommer}@informatik.uni-erlangen.de

***Abstract*—We investigate the impact of the human driver behavior on Intelligent Transportation Systems (ITS). Motivated by early studies, which investigated the driver behavior and which provided a rough classification of different reactions on presented traffic information, we integrated such models into our simulation framework Veins. We were able to determine a significant change in the performance of a technically optimized system due to suboptimal reactions of the drivers. The main objective of this study is to outline the need for integrated driver models into the development process of Traffic Information System (TIS) solutions. Based on our simulation framework, not only the driver model can be accurately represented but we were also able to show that simple probabilistic models show exactly the same behavior compared to sophisticated empirical measurement based ones.**

I. Introduction

We are experiencing a rapid development of efficient Inter-Vehicular Communication (IVC) protocols aiming to enable Intelligent Transportation Systems (ITS) by collecting, evaluating, and sharing relevant traffic information [1], [2]. Recently, numerous approaches have been presented, which take into account the distinct nature of vehicular communication systems, most prominently the large differences in node speed and resulting short interconnection times, as well as predictable node mobility. Focusing on Traffic Information System (TIS) applications, especially beaconing solutions and peer-to-peer based approaches are considered candidates for almost optimal information sharing [3]–[5].

Usually, the developed protocols and mechanisms are evaluated either in a size-limited experiment conducted by volunteering drivers, or in simulation experiments. Whereas the experimental approach allows to study several real-world effects, the limited size of the experiment may also falsify the results. Projects such as simTD[1] are going to provide large-scale experimentation, however, only a limited range of parameters can be evaluated in such a setting. On the other hand, simulation techniques allow performance evaluation of large-scale vehicular networks. With the development of more realistic wireless transmission and mobility models, the quality of the achieved results is considered to match reality quite accurate [6].

It can be said that the development of TIS solutions is currently entering a stage of fine-tuning. However, recently investigated adaptive beaconing approaches as well as peer-to-peer enhanced data management techniques can provide yet another level of efficiency to ITS solutions.

Unfortunately, the technical factors taken into consideration are not sufficient to globally optimize the system. We believe that a major component is missing in many of the technical papers: the interaction of the system with the human driver.

This issue has been considered already in early studies of automotive environments [7]–[9]. Here, driver behavior was identified as a key component. However, this knowledge has seemingly disappeared with the development of distributed information sharing systems, which allow to operate a Vehicular Ad Hoc Network (VANET) as a decentralized database able to update missing information and to always provide a (nearly) optimal route using integrated maps and the available traffic information. It is usually assumed that the driver exactly follows the suggestions provided by the TIS.

Based on classifications of driver behavior available in the literature, we study the impact of human driver behavior on the quality of the TIS as a whole. Furthermore, we integrate these different classes into our simulation framework *Veins* (Vehicles in Network Simulation), to show their impact in selected simulation results, but also to provide a framework that allows to re-evaluate existing ITS solutions.

The objectives and contributions of this paper are twofold:

- We show the impact of the driver behavior on ITS based on a review of early studies in the field (Section II) and based on a simulation study that we conducted for different behavior classes (Sections III and IV).
- Furthermore, we demonstrate that even complex behavior models can be represented using much simpler probabilistic models, finally leading to more realistic simulation studies (Section IV).

II. Related Work on Driver Behavior

The impact of the driver behavior is a topic of interest since the early days of traffic information systems. Actually, some of the most comprehensive psycho-physiological studies have been performed in the late 1980ies or early 1990ies. For example, König et al. developed a model of a driver's behavior using AI techniques for the driver's route planning [7].

Basically, the authors considered four submodels that influence the driver's behavior as shown in Figure 1. The driving behavior comprises the degree of aggressiveness, which can

[1] http://www.simtd.de

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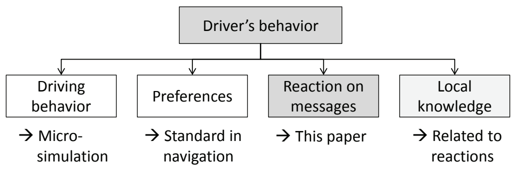

Fig. 1. Driver behavior submodels according to [7]

be characterized e.g. by the driven speed or the frequency of overtaking. Experience, age, and sex also contribute to this classification. In microscopic simulation models like those implemented in SUMO (see Section III), this factor is often integrated. Furthermore, the preferences of the driver generally influence both the selected route (a factor that is integrated into navigation systems today) and the motivation to accommodate changes to this route. Finally, the reaction on received messages and the local knowledge are key elements of the driver's behavior. Local knowledge is difficult to model and also somewhat related to the reaction on received messages. In this work, we primarily consider the reaction on received messages and develop a model taking into account all the related influences. Some of these findings are already part of commercially available navigation systems, e.g. Navigon supports personalized navigation with a learning effect.[2]

The most comprehensive literature study of human factors has been conducted by Dingus et al. to provide guidelines for advanced traveler information systems and commercial vehicle operations [9]. A very interesting aspect identified in this study is that human drivers tend to resist diverting from their present route to avoid congestions, i.e. they prefer following traditionally used routes.

This report also summarizes driver classes that have been identified in earlier work by Barfield and Haselkorn [8], [10], who studied the behavior of commuters. Based on cluster analysis techniques, it is possible to show that four commuter subgroups exist with respect to their willingness to respond to the delivery of real-time traffic information [9, section on driver acceptance and behavior]:

- Route changers – drivers who are willing to change both time and route of the tour depending on traffic information
- Non-changers – people who are absolutely unwilling to change the route
- Pre-trip changers – drivers who are willing to change the route before leaving the house
- In-trip changers – those who are only willing to change just before entering a possibly congested highway

Besides their classification into driver models, experiments have been conducted to investigate the driver behavior w.r.t. presented congestion information and the scale of in-vehicle navigation systems [11]. This more psychologically oriented study outlined some dependencies between drivers' stress level and their reaction on congestion information.

[2]Navigon press release on MyRoutes (March 2, 2009)

TABLE I
BEHAVIOR CLASSES

Class	Description	Mix	All
Always	route selection according TIS recommendations	40.1 %	20 %
Never	drivers unwilling to change the route	23.4 %	20 %
$d < D$	route changes only if the distance to the congestion is less than D	20.6 %	20 %
$d > D$	route changes only if the distance to the congestion is larger than D	15.9 %	20 %
P	probabilistic decision whether to fall into class *always* or *never*	0 %	20 %

In the field of ITS, mainly research has been conducted on traffic signal control and its impact on the driver's route choice [12], as well as on intersection management [13]. It became obvious, that the driver's behavior is of great interest for intelligent traffic light systems.

Many of the results have recently been incorporated into an edited book [14]. This book is also a great reference on psychological models that influence the driver's safety, such as the use of entertainment related devices or the interaction with the navigation system. Especially, the chapter by Panou et al. should be mentioned, which summarizes international research projects related to modeling the driver behavior [15].

III. Behavior Classes and Integration into Veins

In the following, we summarize the selected behavior classes, which are essentially motivated by Dingus et al. [9]. Furthermore, the integration in our simulation framework *Veins* is outlined.

A. Selected behavior classes

We focus on four basic classes of driver behavior as well as three combinations thereof. The first four can be considered typical behavior according to the published psychological studies: A driver following all TIS recommendations falls into the class *always*. This is basically the kind of behavior that is being assumed for almost all simulation and experimental studies of ITS solutions. The second important class is *never*, in which the driver continues his every-day procedure and completely ignores the TIS. This class must be clearly distinguished from the frequently used penetration rate. Even though the driver does not follow the advice, the car can certainly take part in the distributed TIS. The third class contains all drivers who only consider congestions within a certain range $d < D$ as relevant. They simply assume that there will be enough time to clear the congestion. Finally, a fourth class represents drivers who want to bypass a congestion on a long detour, but also make sure that they will not have to stop in secondary jams due to short term detours, thus this class is represented by $d > D$.

All the classes are summarized in Table I. This table also includes the combined classes of driver behavior. A *probabilistic* class selects the driver to follow either the *always* or the *never* model at time of starting the journey, based on

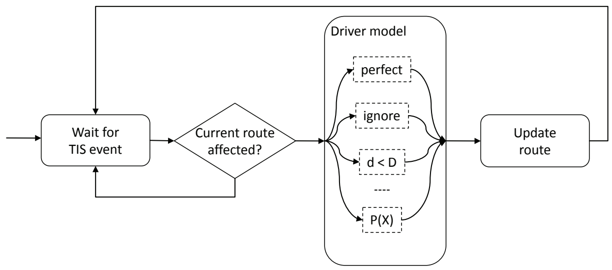

Fig. 2. Integration of the driver behavior classes into the TIS application

a given value of P. The class *mix* is a representation of the driver model in [9]. Finally, the class *all* is a combination of all the simple classes together with the probabilistic decision.

B. Integration into Veins

We implemented all the listed classes of driver behavior within our *Veins*[3] simulation environment [16]. *Veins* is an integrated simulation relying on OMNeT++[4] for the network simulation including the wireless communication channel, the data dissemination protocol, and the TIS application. The vehicles' mobility is modeled with the help of the SUMO[5] traffic microsimulation. SUMO already supports the use of appropriate maps (including those from the *OpenStreetMap* project) and simulates the mobility of each vehicle independently using the Krauss car following model and an associated lane change model. The driving behavior is implemented in form of a configurable degree of aggressiveness. Both simulators are bidirectionally connected by the TraCI interface [16], [17], which is also providing route-related information to the driver behavior model as outlined below.

We integrated the presented classes of driver behavior into the OMNeT++ side, as the driver behavior mainly influences the TIS application. Figure 2 outlines the necessary procedures. After receiving a TIS event, the system checks the driver's class and whether this class allows to react on the received TIS message in a function `BeaconApp::reactOnTisData()`. If the driver model allows route recalculation, a command is issued to let SUMO recalculate the path based on the new information. The distribution and exchange of TIS data with other cars is not affected.

The only part of the driver behavior model that does not follow the layered structure is the estimation of the remaining distance to the destination. As this information is obviously not available in the network simulator, the SUMO microsimulation framework has to be queried. This can be done using a recently implemented TraCI interface command `commandDistanceRequest(src, dest)` to calculate the shortest distance between any two points on the given map, in our case using the current position `getPosition()` as the starting point.

[3]http://www7.informatik.uni-erlangen.de/veins/

[4]http://www.omnetpp.org/

[5]http://sumo.sourceforge.net/

TABLE II
COMMON SIMULATION PARAMETERS

Parameter	Value
beacon interval	1 s or 10 s
processing delay	1 ms to 10 ms
channel bitrate	$11\,\mathrm{Mbit\,s^{-1}}$
approx. transmission radius	180 m
vehicle mobility model	Krauss
max. speed	$14\,\mathrm{m\,s^{-1}}$
max. acceleration	$2.6\,\mathrm{m\,s^{-2}}$
driver imperfection σ	0.5
max. deceleration	$4.5\,\mathrm{m\,s^{-2}}$
vehicle length	5 m

In summary, the model of the driver behavior represents a psycho-physiological view of the decision process by the driver. Even though the used calibration (Table I) is based on rather old information, we will show that the driver behavior has a non-negligible effect on the TIS as a whole. As soon as new empirical data becomes available about the driver's behavior and its interaction with the TIS, the calibration can be updated without modifying the model.

IV. Simulation Results and Discussion

For the evaluation of the influence of the different driver classes, we prepared two typical simulation setups. As can be seen from the results, the performance of the TIS application significantly changes for different classes and models. We also show that complex models as those discussed in [8], [9] can be closely matched by simple probabilistic models.

A. Simulation setup

We configured *Veins* for two basic scenarios. First, as a baseline reference, we used a grid scenario in which cars are entering the playground on the top-left corner and drive through the grid to the bottom-right corner. To study more realistic mobility, a second scenario represents a part of the city of Erlangen. Cars are starting at the CS department driving to the city center. In both scenarios, an artificial accident is scheduled to study the behavior of following cars in the case of a road congestion. For TIS data exchange, a simple beacon protocol is used with fixed beacon intervals of 1 s and 10 s, respectively. Whereas this protocol is probably not optimal for all situations, it covers at least the extreme situations well: the 1 s interval for fast TIS exchange and the 10 s interval for reduced network congestion. The configured protocol parameters are summarized in Table II.

For the driver behavior, we studied all the discussed classes, both the uniform and the combined ones. The distance-based decisions were analyzed with two reasonable threshold distances of $D_1 = 1\,\mathrm{km}$ and $D_2 = 2\,\mathrm{km}$. Also, for the probabilistic classes, two probabilities for a vehicle to fall into class *always* were examined: $P_1 = 0.5$ and $P_2 = 0.7$. We selected these probabilities based on empirical studies using different scenarios and simulation setups. Certainly, for updated complex psycho-physiological models, these threshold probabilities need to be updated.

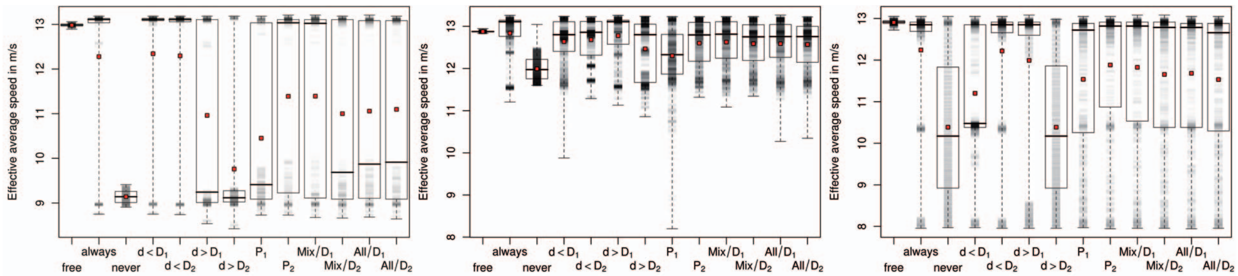

Fig. 3. Statistical analysis of the driver behavior models for a small grid (left), large grid (middle), and the Erlangen scenario (right)

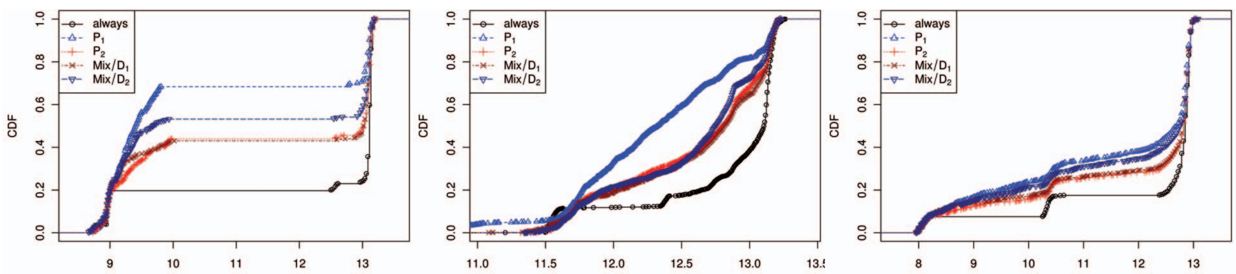

Fig. 4. CDF of the average speed achieved for the driver behavior models for a small grid (left), large grid (middle), and the Erlangen scenario (right)

B. Results

As the key metric to study the driver behavior, we chose the travel time represented by the effective average speed of the vehicles. This measure is frequently used to show the capabilities of TIS applications and IVC protocols. Furthermore, we recorded only the measurements for cars that entered the setup until the artificial congestion had been resolved. As a baseline measure, we also examine the metric in an accident *free* scenario.

Figure 3 shows the statistical analysis of the observed results for the $1\,\text{s}$ beaconing. The figure shows a boxplot indicating the median as a thick line in the middle of the box, the 1st and 3rd quartile are represented by the box' lower and upper end, respectively. Furthermore, the individual measures are plotted as grey bars in the background, thus, the darker the area, the more measurements fall into this region. Finally, the mean is plotted as a small red box. As can be seen, the statistical behavior of the measurement results is quite different for the *always* class compared to the different driver classes. Also, the single classes are either too optimistic or pessimistic compared to the mix representing typical driver behavior as presented in the literature. Whereas it could be questioned whether the grid scenario is representative, the Erlangen city scenario also indicates the same behavior.

To study the impact of the IVC protocol, Figure 5 shows the results for the large grid for the $10\,\text{s}$ beacon interval. We selected this sample, because the graphs for the other scenarios show almost no change compared to the $1\,\text{s}$ beaconing. Even though the results deviate from those for $1\,\text{s}$, the general behavior is similar. We can analyze the behavior of the different driver models, and thus the impact on the technically optimized ITS, even better in the CDF plot shown in Figure 4. As can be seen, the lower black curve clearly deviates from the other curves. Thus, the behavior of the system as a whole cannot be represented by the typically used *always* model.

Another remarkable result is that all the shown measures seem to indicate that the probabilistic model behaves quite similar compared to the mix models. To study this effect in more detail, we plotted QQ plots as shown in Figure 6. The closer the points are matching the diagonal line, the closer the models match. As can be seen, $P_2 = 0.7$ seems to model the mix quite accurate for all scenarios. The key advantage of this finding is that complex models in experiments and simulations can be substituted with a probabilistic decision system with only minor impact on the results.

Even though the presented results are already showing that the driver behavior must be accommodated in ITS performance evaluations in order to obtain realistic results, we created an additional scenario that adds further complexity to the Erlangen city scenario. We introduced additional cross traffic that interacts with the initial vehicle flow in the scenario resulting in a large number of micro jams. The results of this evaluation are shown in Figure 7. Again, most of the discussed trends and effects can be confirmed. The probabilistic model P_2 is

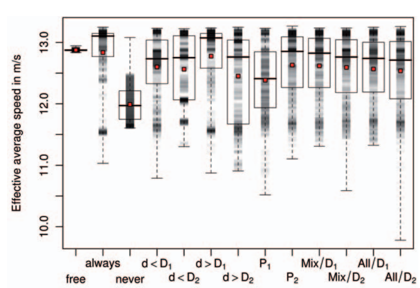

Fig. 5. Statistical behavior for the large grid and $10\,\text{s}$ beaconing

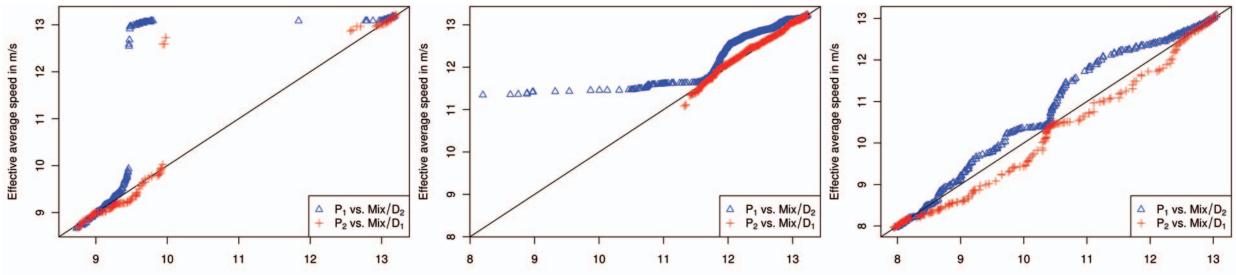

Fig. 6. QQ plot of probabilistic vs. mix models for a small grid (left), large grid (middle), and the Erlangen scenario (right)

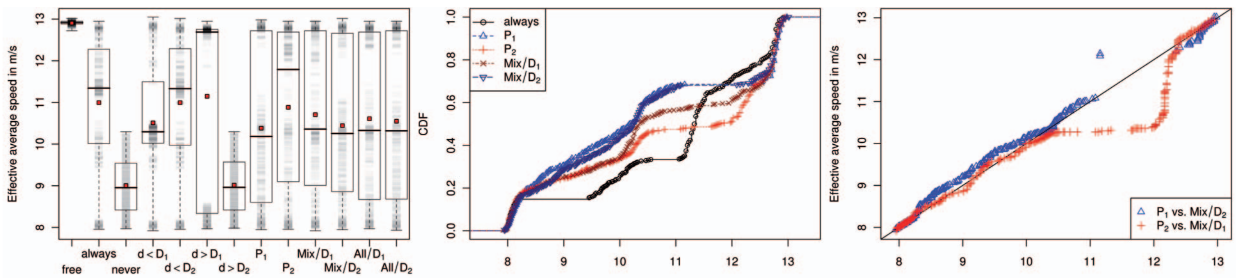

Fig. 7. Erlangen scenario with additional cross traffic: statistics, CDF, QQ plot

not matching as close as shown for the other measurements. However, as can be seen from the CDF, the number of non-matching measurements is extremely small.

V. Conclusion

We investigated the impact of human driver behavior on the quality of ITS. The presented results clearly indicate the need to use realistic driver models, especially w.r.t. TIS applications. The presented solution, which has been integrated into the publicly available *Veins* framework, allows to run integrated simulation experiments taking the driver's behavior into account. An astonishing side effect is that simple probabilistic models can be used to represent complex empirically generated models quite well. Whereas we believe that updated data to base driver classification on is needed (the current set is mainly based on investigations using very early TIS approaches), new results can easily be integrated into the presented simulation framework.

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