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SIMULATION ASSESSMENT OF NEW GENERATION NAVIGATION STRATEGIES

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ABSTRACT

Probe vehicle (or connected car) data are becoming an important source of real-time travel information for a variety of intelligent transportation system applications. Since traditional sensors have significant installation and maintenance costs, technological companies are interested in traffic data from these alternative detection techniques for computing traffic-aware shortest routes. This paper analyzes and evaluates the use of data provided by probe vehicles in two reactive navigation strategies and how this affects a set of city and driver key performance indicators. The case study adopts a microscopic simulation approach to emulate real-size fleets of probe cars providing positions and speed data. The paper presents and discusses the modeling approach and the obtained results after conducting an experimental design for a Barcelona district scenario. Moreover, a simulation-based framework is introduced for simplifying the analysis of simulation results and easily visualizing origin-destination paths for the proposed driver segments (experts, regular, and tourists).

1 INTRODUCTION

In urban areas, connected vehicles are expected to reach high concentrations in the immediate future. The market of connected vehicles is booming and both academia and the automotive industry are promptly responding to its requirements. In fact, there is a broad consensus on the new family of services that will be enabled by the advances in vehicle-to-vehicle communication.

The use of probe vehicle data (PVD) has been investigated in some research projects, such as Mobile Millenium or CarTel (Hull et al. 2006), which included a pilot traffic-monitoring system using the GPS in cellular phones to gather traffic information, process it, and distribute it back in real time to the phones. Products and companies performing mobile crowdsourcing (Google Traffic, INRIX, and TomTom Traffic) allow for real-time data gathering.

The capabilities to effectively monitor traffic conditions have been studied from early considerations of equipped vehicles as a mobile sensor network (Hull et al. 2006) to more recent surveys (Lee and Gerla 2010; Bessler and Paulin 2013). However, most analyses have been conducted from the perspectives of either continuous monitoring of the vehicle state or driver safety, while some others have considered the potential guidance offered by such mobile sensing (Lorkowski et al. 2003; Lee and Park 2008; Wang et al. 2017). This last area of analysis is the scope of the current paper.

Without trying to be exhaustive, the impact of route guidance on travel time, environment, and safety has been investigated (Oh and Jayakrishnan 2002; Paikari et al. 2013; Olia et al. 2016), usually in relation to its benefit under incident conditions and while quantitatively assessing the potential impacts of real-time routing guidance and advisory warning messages to guided vehicles. Some other authors have analyzed reactive policies (Deflorio 2003) using simulation and proactive route guidance (Pan et al. 2012). Nevertheless, in some of these studies, the elaboration of traffic state estimation has been treated from a simplistic point of view or has not been described in depth. For example, Pan et al. (2012) use Greenshield's model to estimate travel times in road segments, but this approach does not seem suitable for urban networks and details are not included.

The aim of this paper is to present an experimental design for simulation assessment of navigation strategies based on PVD while considering driver behavior and route choice models. Moreover, a simulation-based framework is introduced for simplifying the analysis of simulation results and easily visualizing them. The conceptual framework is briefly described first, and a section follows describing in detail the emulation of the different concepts included in the Custom Module. After that, we describe the simulation experiments for a large fleet of PVDs according to penetration rates and additional factors considered in the experimental design. The next section provides an analysis of the results and the paper ends with our conclusions and future research.

2 CITSCALE: A SIMULATION TESTBED FRAMEWORK

The CitScale tool (Linares et al. 2017) is a software platform developed by inLab FIB at Universitat Politècnica de Catalunya (UPC) for visualizing, analyzing, and comparing experimental designs that model urban traffic scenarios. Assessments of new mobility concepts and new automotive vehicles are the main targets of projects that use CitScale (Montero et al. 2017). In particular, in this paper, this tool offers the possibility of enabling a new family of services based on the previously mentioned advances in inter-vehicular communications. In particular, the proposed case study aims at evaluating the effect of using probe car fleet data at different penetration levels to develop real-time navigation strategies for connected vehicles.

Figure 1 shows the proposed simulation testbed framework that is composed of an Executions Controller, a Traffic Simulation Module, a Result Preparation Module and a Visual Analytics Module. The core components of the CitScale analytics platform are the graphical interface and the traffic simulation model. The traffic simulation component includes a microscopic traffic simulator and a set of custom modules and functions that were developed using API extensions.

The analysis of simulation results is performed by two fundamental and independent components: the Result Processing Module and the Visual Analytics Module. One deals with the automated preparation of data and the other with operating the data display. The Result Processing Module makes the entire pre-processing of data automatically, thus allowing the Visual Analytics Module to automatically use the simulation results directly, without the need for any manual update.

The visualization and analysis tool has been implemented using the Shiny web application (RStudio Project 2018) for R that simplifies the development of interactive web applications. The Shiny web application is agnostic to the traffic simulation platform. If we are going to emulate smart city policies by necessarily evaluating new vehicle types, probe vehicle sensors, navigation strategies and innovative mobility concepts such as multiple passenger ridesharing, then several ad-hoc components in the traffic simulation model must be programmed using API extensions. However, any microsimulation platform that allows API extensions can be used.

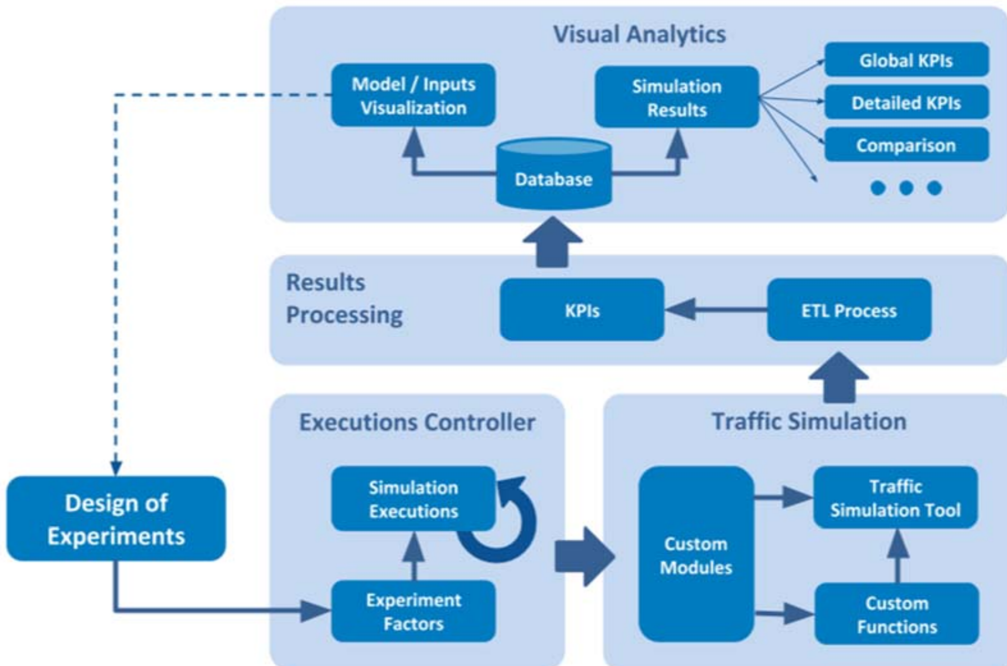

Figure 1: Simulation Testbed Architecture.

In this work, an Aimsun (Transport Simulation Systems 2018) model was available from previous projects. Aimsun functional architecture and the interaction libraries support the extended modeling utilities that are required. The exchange of information between the API applications and the micro-simulator can be made at every simulation step (0.5 sec). The programming languages in which Aimsun provides its API are C++ and Python. While Python is used to easily collect some of the data, C++ is needed for emulating the probe vehicles due to performance reasons.

3 CUSTOM MODULES IMPLEMENTATION

The proposed case study requires detailed driver behavior, heuristic route choice modeling that depends on knowledge of the network and congestion, and the availability of navigation data. Traffic microsimulation capabilities are needed to achieve the final goal.

In order to extend the standard functionalities of the selected microsimulation tool so that it can deal with the requirements of this case study, the next items have been implemented into the Custom Modules: PVD emulation, driver behavior modeling, navigation strategies, and time-dependent link and lane travel time estimation module.

3.1 Probe Vehicle Data Emulation

The objective of this module is to emulate vehicles with equipped sensors connected to a Traffic Management Center. This paper assumes that the Vehicle-to-infrastructure (V2I) and Vehicle-to-vehicle (V2V) technology is on board of probe cars (Montero et al. 2016). The collected data were filtered to remove any incomplete observations or outliers. Then, these data were used to calibrate the emulation of the PVD module included in the Traffic Simulation Module.

The main aim of this paper is to emulate probe car ‘real-time data’ use in connected car guidance under different levels of probe vehicle penetration. To this end, only basic vehicle sensors have been assumed, allowing at each simulation step data for vehicle position and speed.

3.2 Driver Behavior Modeling

This paper highlights driver behavior modeling, which has not been considered in any related papers in the literature (Lee and Park 2008; Wang et al. 2017; Paikari et al. 2013; Olia et al. 2016; Deflorio 2003; Pan et al. 2012; Minelli et al. 2015). Drivers are split into six groups according to their knowledge of network and traffic conditions and according to guidance availability:

- Expert drivers: those who know the network and historic traffic conditions for the selected horizon of study. They are modeled with route choice selection and proportions following experienced travel times that satisfy dynamic user equilibrium (DUE) (Chiu et al. 2011) by assuming a historic demand pattern. DUE paths and proportions are loaded in the simulation environment from a pre-calculated binary file.
- Regular drivers: those with knowledge of the network and historic traffic conditions for recurrent trips (50% randomly selected), but who use main streets based on free-flow for non-recurrent trips (50%).
- Tourist drivers: those who have limited knowledge of network and traffic conditions and use K-shortest paths algorithm based on the main streets.

Finally, Guided drivers constitute a design-dependent proportion for any Expert, Regular, or Tourist driver class, and they are modeled with a 100% acceptance of navigation advice.

Expert and Regular drivers exhibit driving characteristics related to the car-following model, such as reaction times, desired speed and acceptance of speed limitations. According to the calibrated profile of Barcelona drivers: Reaction Time (1.0s); Reaction Time at Stop (1.35s); Reaction Time at Traffic Light (1.35s); Speed Acceptance and Minimum Inter-Vehicular Distance are assumed to be truncated normally distributed with the former having mean-1.1, sd-0.1, min-0.9 and max-1.3, and the latter having mean-1.0m, sd-0.3m, min-0.5m and max-1.5m.

Tourist drivers behave roughly with a 25% increment in reaction times, means and limits (same standard deviation), and they strictly adhere to the speed limits, while Minimum Inter-vehicular Distance is truncated normally distributed with mean-1.25m and sd-0.1m – between 0.75 and 1.5 m.

3.3 Navigation Strategies

An interesting discussion about route guidance assessment can be found at Wang et al. (2017). A navigation application is modeled as being available to a certain percentage in each driver class. Three navigation strategies are implemented according to the simulation platform possibilities:

- Free-flow K-shortest paths when probe vehicle fleet is not available.
- Stochastic Route Choice considering instantaneous traffic conditions inferred from data provided by PVD. They are modeled from estimated instantaneous K-shortest travel time paths. They can be either link-based, according to user-defined link costs (link travel time estimates from PVD), or lane-based, according to user-defined stream costs (lane travel time estimates combined into a stream travel time).

  To consider dynamic and instantaneous travel-time-based route choice, 100% re-routing is enabled every time window interval.

The critical point is that a real-time routing strategy for connected cars (guided) is applied from the travel times provided by the floating car data. Travel time estimates used in K-shortest path calculations might depend either on lane-based or overall link-based travel time, both of which rely on PVD sent to a centralized system. Travel times between points of interest can be inferred according to Origin-Destination (OD) path travel times and route-choice proportions to feed Kalman filtering formulations proposed by the authors to estimate dynamic OD matrices.

3.4 Link and Lane Travel Time Estimation Module

In order to estimate time-dependent lane and link travel times, a proposal based on (Sanaullah et al. 2013) has been considered. This approach involves a time-window concept, which is an experiment design factor that represents the time interval in which travel times are being updated. Therefore, with a greater time-window, the probability of finding lanes and links with available data grows.

The simulator can gather probe vehicle data (such as position and instant speed) at every simulation step (0.5 seconds). For our experiments, the time-window parameter choice is 2 seconds, which means that probe vehicle data are being collected periodically after this interval of time. This assumed time-window is adequate in order to ease computational and memory costs.

The implemented approach for estimating travel time considers three different cases for every lane.

a) Case in which there are **no** PVD in the last time window.
b) Case in which there are PVD from just **one car** in the last time window.
c) Case in which there are PVD from **more than one** vehicle in the latest time-window.

In case (a), travel time estimation is the same as the lane travel time of the most recent time window. If there are no data available, the lane travel time is set to the time corresponding to a free flow situation.

In case (b), the following method is applied:

- Let tt_1 be the estimated travel time for the fraction of the lane until the first detection of the vehicle. Therefore, tt_1 is the length of this lane fraction divided by the vehicle's instantaneous speed at the first observation in this lane. Intuitively, it is the travelled distance on the lane, which gives a time magnitude.
- Let tt_L be the difference (in seconds) between the first and last detection intervals.
- Let tt_2 be the estimated travel time for the last fraction of the lane since the last detection of the vehicle. Similarly as tt_1, tt_2 is computed as the distance from the last observation at the beginning of the next section divided by the probe vehicle's instantaneous speed in the last observation (detection interval) of the time-window.

Then, the travel-time of the considered lane is $tt_1 + tt_L + tt_2$.

In case (c), a weighted travel time of the lane is computed considering all vehicles. Supposing there are n cars providing data in the lane, $\frac{1}{n}\sum_{v=1}^{n} w_v tt_v$, where tt_v is the travel time of a car calculated as explained in case b), and the weight $w_v \in [0, 1]$ is the fraction of the section length where probe vehicle v is detected in the lane.

On the other side, the link travel time estimation from PVD is computed as the mean of travel times for streams. Lane travel time estimation is performed combining stream travel times with the information about the allowed turns.

4 DESIGN OF EXPERIMENTS

The selected scenario is the Barcelona Central Business District, known as "L'Eixample" (Montero et al. 2016), which comprises 7.46 km^2 and 250,000 inhabitants. The horizon study is 1h, accounting for 42,500 trips. Passenger car demand is modeled as 15-min time-sliced demand whose OD pattern reproduces the 9-10h morning period in L'Eixample.

4.1 Design Factors

The factors considered in the design of the simulation experiments (Table 1) are:

- **Driver Type Distribution** (TD factor) into Expert-Regular-Tourist.

- **Guidance Penetration** (GP factor). Connected cars percentage of cars whose route choice decisions follow those advised by a navigation tool fed by PVD.
- **Demand Pattern** (DP factor) into 4 levels referring to a perturbation of the historic demand pattern in OD pairs belonging to the fourth percentile trip distance (according to Manhattan distance). They account for 42,500, 44,600, 46,860, and 48,600 trips, respectively. 0% means historic demand pattern.
- **Probe Vehicle Penetration percentage** (PVD factor) modeled common to any driver type into 8 levels. Base level is 0%. It indicates route guidance based on free-flow travel times. An additional Ground Truth level consisting of travel time estimates directly from 'simulated Ground Truth' was also included in some initial experimentation.
- **Navigation Strategy** (NS factor) modeling driving recommendations based on either lane-level or link-level PVD when PVD are available. Base level is lane-level, when 0% PVD is set, free flow travel times are assumed.
- **Time-Window length** (TW factor) is the rolling horizon interval considered for the estimation of traffic variables from PVD. TW is not affected when 0% PVD is set.

Table 1: Design factors description.

Design Factors	Factor Levels	Base Level	Alternative Levels
Driver Type Distribution	expert-regular-tourist	40-50-10 (%)	20-70-10, 40-40-20, 60-20-20 (%)
Guidance Penetration	guided-nonguided	0-100 (%)	10-90, 20-80, 30-70, 50-50, 70-30, 80-20, 90-1(100-0 (%)
Demand Pattern		0 (%)	10, 20, 30 (%)
Probe Vehicle Penetration		0 (%)	10,20,30, 80, 90, 100 (%) and PI (perfect info)
Time-window Length		3min	1.5min, 6min

4.2 Collected Key Performance Indicators

In general, on microscopic traffic simulation platforms, the default statistics are very rich. Statistics have been collected every 90s and stored in an SQLITE database for each replication. Driver Key Performance Indicators (KPIs) collected for each Expert, Regular, and Tourist driver type (either guided or non-Guided) are shown in Table 2.

Table 2: Driver KPIs.

KPI	Unit
Average Delay while covering 1 km	s/km
Average Speed per vehicle	km/h
Average Travel Distance per vehicle	Km
Average Travel Time per vehicle	Min
Average Travel time to cover 1 km	s/km

Network KPIs (Table 3) are global statistics (all driver classes) and cover the whole simulation horizon. From a driver satisfaction point of view, the critical KPI is considered to be the average travel time (min), but also for researchers interested in the assessment of travel times between Points of Interest (POI) inferred from PVD. A detailed analysis on the base scenario for all design factors found that five replications facilitate a global 5% relative precision in average travel time at 95% confidence for any driver type, while the greatest absolute error was about 1/3 min for the tourist driver type.

For computational reasons, running the full factorial design is unfeasible since 3,072x5=15,360 replications would be needed. Therefore, the first set of experiments was constrained in order to identify non-aliased factor main effects according to the Fedorov algorithm (Fedorov 1972) for optimal designs: 29 experiments were given (thus, 145 replications were executed, each one taking around 2h in an Intel Core i7-4790 CPU (frequency of 3.6GHz)-4 cores-8GB DDR3 Memory and Windows 8.1 (x64 system)).

Table 3: Network KPIs.

KPI	unit	ACRONYM
Average Flow	veh/h	mflow
Average Speed	km/h	mspeed
Average Travel Time to cover 1 km	s/km	mtt.s.km
Density	veh/km	density
Fuel Consumption	l	fuelc
Mean Delay Time while covering 1 km	s/km	mdelay.s.km
Throughput Rate (completed trips/total demand)	%	thrputrate
Total CO2 emissions	kg	CO2
Total NOX emissions	kg	NOx
Total Travel Distance	km	ttdis
Total Travel Time	h	ttt.h
Number of vehicles lost in system.	vehs	virlostin
Number of vehicles lost out system.	vehs	virlostout
Number of vehicles waiting to enter into the system.	Vehs	virwait
Waiting Rate = VirWait /Demand	%	waitrate
Number of vehicles inside the network	vehs	tvehin
Total number of vehicles that have entered the system	vehs	inputveh
Demand = inputveh + virWait	vehs	demand
Total number vehicles that have exited the system	vehs	tvehout

5 SIMULATION RESULT ANALYSIS

Traffic simulation platforms provide a wide extend of KPI results. In this work, we have selected a few KPIs that were considered relevant for the evaluation of navigation systems. Nevertheless, KPIs cannot be considered isolated, because they are strongly correlated. Figure 2 on the top shows the Spearman coefficient of correlation (non-parametric statistic for the linear association between non-Gaussian numeric variables) between selected KPIs. It can be seen that most of the cells show an absolute value of Spearman correlation greater than 0.5, so a monotonic relationship appears among most KPI pairs. For example, demand (total demand trips, trips entering plus waiting to enter in the system) and mtt.s.km (travel time to cover one km) show a positive Spearman correlation of 0.77 indicating a direct relation: as the total number of trips increases, the travel time per km also increases, because traffic congestion gets worse. A normalized principal component analysis (PCA) has been addressed to discover the latent principal component or factorial axes that represent non-correlated effects. PCA is a statistical procedure that uses an orthogonal transformation to convert a set of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Normalized PCA has been selected to account for different scales of available KPIs and graphical results can be seen at Figure 2 on the bottom. Almost 90% of the total variance in the variables are explained by the two first principal component variables. The first axis accounts for 60% of the total variance and divides the KPIs into two subsets: throughput rate and speed opposed to demand and density KPIs, meaning that increasing total demand does mean decreasing the percentage of completed trips (throughput decreases) and also implies decreasing mean speed (due to more vehicles in the network and thus congestion effects). Total travel time (ttt.h) and demand (total vehicles) vectors in Figure 2 on the bottom show a low angle meaning a high correlation between them, which it is meaningful in terms of transport analysis.

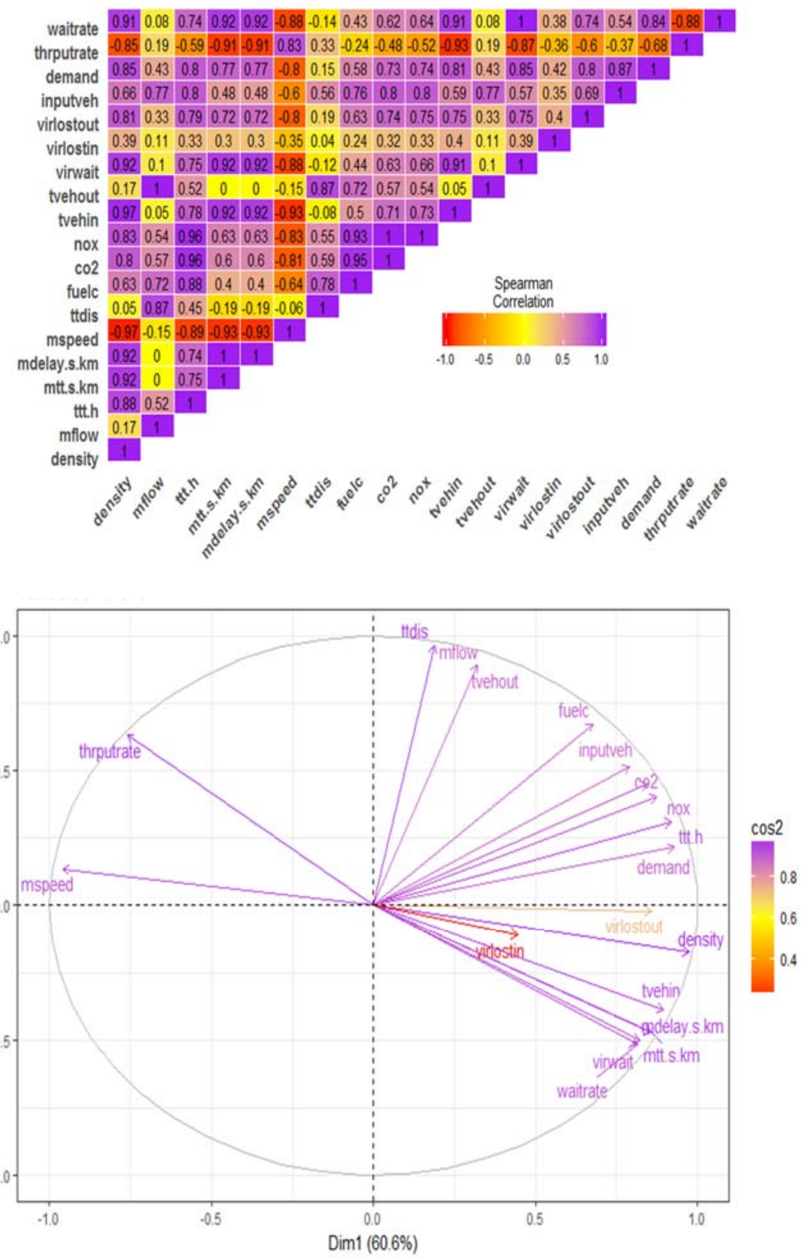

Figure 2: Assessment of correlation between system KPIs obtained by simulation using PCA. Top: Spearman correlation for network KPIs; Bottom: Results of normalized PCA

On the second axis and orthogonal to the first one (see Figure 2 on the bottom), total travel distance (ttdis) and total completed trips (tvehout) show a high correlation between them, but the total completed trips vector is almost orthogonal to virwait variable, total vehicles waiting to enter to the network; this last variable (virwait) is very correlated to mtt.s.km, density and delay.s.km that clearly reflect congestion level leading to the conclusion that despite congestion by increasing total travel distance, the number of completed trips seems to be not affected. Navigation strategies seem to play a role of increasing total travel distance in order to increase the number of completed trips (tvehout).

Congestion conditions are represented in the first factorial axis. Positive values to the right (Figure 2 on the bottom) indicate high congestion and negative values represent higher speeds and lighter congestion. At the end of this section, we focus on delay while covering a km (delay.s.km) KPI, since it is a sensitive indicator of congestion, intuitive and with a high quality representation under the first factorial axis.

Figure 3 shows some KPI results for a subset of experiments defined by the base-level composition of driver population (Expert-Regular-Tourist), a 20% guidance penetration (GP), a demand level that assumes a 20% increment of the historic demand – as a consequence, the knowledge of recurrent congestion by expert drivers makes them to take non-optimal routes once historical conditions are altered. The time-window (TW factor) for data collection and elaboration of travel time estimates is fixed to 3 min. The Factors PVD and NS take different levels (non-exhaustive) and relative values for density, flow, travel time per km, delay per km, speed, total travel time, fuel consumption, and CO_2 and NOx emissions are calculated taking as reference a link-based navigation and 0% GP level. Clearly, density reduction is greater in lane-based scenarios than link-based ones. The same conclusion holds for travel time per km and delay per km (both in seconds). Speed increment is greater in lane-based scenarios than link-based.

Drivers	Navigation Penetration	Demand Pattern	Connected Car Penetration	Time Window	Navigation Strategy	density	mflow	ttt.h	mdelay.s.km	mspeed	ttdis	fuelc	CO2	NOx
40-50-10	20	20	0	3	Link Navigation	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
40-50-10	20	20	**10**	3	Link Navigation	-4,53%	1,67%	-5,48%	-7,89%	1,17%	3,14%	1,47%	0,41%	0,11%
40-50-10	20	20	**20**	3	Link Navigation	-6,64%	3,07%	-6,33%	-9,12%	1,42%	4,75%	2,51%	0,44%	0,17%
40-50-10	20	20	**30**	3	Link Navigation	-5,66%	1,94%	-7,28%	-10,47%	2,53%	3,63%	0,80%	-0,26%	-0,43%
40-50-10	20	20	**100**	3	Link Navigation	-9,15%	3,30%	-9,12%	-13,17%	3,32%	4,96%	1,08%	-0,95%	-1,45%
40-50-10	20	20	**Perfect Info**	3	Link Navigation	-8,93%	3,91%	-8,08%	-11,72%	2,62%	5,37%	1,94%	-0,48%	-1,04%
40-50-10	20	20	0	3	**Lane Navigation**	-5,08%	0,96%	-4,01%	-5,80%	1,74%	1,23%	-0,98%	-1,70%	-1,86%
40-50-10	20	20	**10**	3	**Lane Navigation**	-8,14%	3,30%	-8,34%	-12,07%	2,75%	5,69%	2,22%	0,10%	-0,12%
40-50-10	20	20	**20**	3	**Lane Navigation**	-10,33%	3,76%	-9,67%	-13,97%	3,70%	6,04%	1,61%	-0,89%	-1,31%
40-50-10	20	20	**30**	3	**Lane Navigation**	-9,80%	2,48%	-11,17%	-16,13%	4,63%	4,43%	-0,87%	-2,04%	-2,23%
40-50-10	20	20	**100**	3	**Lane Navigation**	-12,85%	4,63%	-11,61%	-16,79%	4,90%	6,77%	1,25%	-1,90%	-2,45%
40-50-10	20	20	**Perfect Info**	3	**Lane Navigation**	-9,95%	3,14%	-11,52%	-16,63%	4,56%	5,05%	0,09%	-1,66%	-1,94%

Figure 3: KPI figures for comparison to the basic scenario (first row): lane- vs. link-based navigation.

Dark cells in Figure 3 are remarkable since they refer to total travel distances (ttdis column), showing an increment on total travel distance when the PVD level increases, either in lane-based, or link-based scenarios that has to be properly assessed. The total travel distance is an absolute KPI and depends on the number of vehicles entering the network during the simulation period (inputveh column) that was checked to increase, although not shown in Figure 3, leading to an increase of total travel distance. Thus, this does not have to be interpreted as a drawback of increasing probe vehicle penetration. Emissions seem to slightly reduce as PVD penetration increases (improving the amount of data for travel time estimation), but reductions are not very important. Fuel consumption results are not conclusive, but a modest increment can be expected which can be justified attending to the increment of total travel distance that occurs when diverging to longer routes (in length) suggested by the navigation system. Rows linked to 0% PVD are interesting, because navigation strategies in this case are fed with free-flow travel times leading to inaccurate shortest paths (in time) for guided vehicles and show that lane-based navigation strategy outperforms results obtained for link-based navigation.

The linear model relating design factors to mean delay per km has a coefficient of determination of 97% and all factors are statistically significant indicating the net-effect of all design factors. GP, PVD, and DP are the most significant factors and TW shows less significance (10^{-6}). According to Figure 4, as guidance penetration increases, mean delay per km decreases up to 30%, then it becomes stable and for a 100% guidance penetration slightly increases. Reduction in delay per km (s) from a non-guidance situation to a 30% guidance situation is remarkable – 35% reduction. This is an important result that indicates that guidance assistance is globally useful for the system and seems to benefit guided and non-guided vehicles. As PVD penetration increases, the quality of travel time estimates used to calculate reactive shortest paths for drivers that are navigation users seems to increase and the outcome in the global system is a significant decrease in mean delay per km that reaches a minimum when PVD is 90%.

The demand pattern factor is also very important, as one might expect, since it defines the total number of trips wishing to travel over the network and common sense knowledge is confirmed with simulation results: as demand increases, mean delay per km increases as more congestion is present in the network. The NS factor is the critical factor in this research, since new navigation strategies based on lane-specific data are the aim of this paper and results confirm that lane-based navigation advise produces a reduction in mean delay per km. Thus, perception of congestion is reduced and results point to a promising improvement of 7% reduction in delay. Speed, travel time, and travel time to cover one km are alternative KPIs that have been analyzed and – for all of them – a lane-based navigation advise indicates a benefit over traditional link-based navigation. A 30% GP seems to be the lower penetration rate to obtain global benefit for the whole population of drivers. According to the PVD marginal plot in Figure 4, a 10% PVD penetration seems to be too low to get a global benefit in terms of congestion.

6 CONCLUSIONS AND FUTURE RESEARCH

In this paper, an approach consisting of a general framework and simulation architecture is used for emulating and evaluating general probe vehicle fleets and navigation strategies. The research carried out relies on a detailed simulation of the proposed driver classes and two reactive navigation strategies that have been revealed to be advantageous for guided and non-guided cars from 30% of guided vehicles. We conclude that any mobility service assessment must take into account several KPIs, since these are very correlated. Our simulation results confirm that a lane-based navigation strategy represents an average benefit for the population of drivers, either guided or non-guided, of 5-10% for the most-affected KPIs (travel time, travel time per km, delay per km, speed). With respect to the benefit for specific driver classes analysis, in recurrent traffic conditions, navigation devices are not suitable for expert drivers, but they benefit from the use by other drivers. As a final remark that points to future research, data collected from probe vehicles have been proven to be useful for travel time estimates that are the base of shortest path routing provided by navigation strategies. Probe vehicle data are concluded by our simulation experiments to provide reliable travel time estimates to be included in dynamic OD matrix adjustment procedures as Kalman filtering schemes to simplify the space-estate model or SPSA formulations.

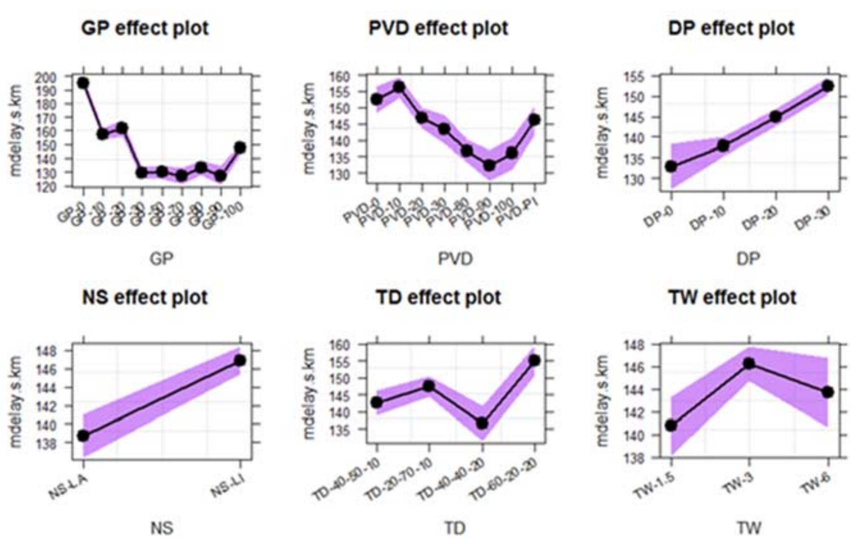

Figure 4: Main effects on delay-time (seconds per km) of experimental design factors: all experiments (95% confidence bands).

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