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Automotive Communications in LTE: a Simulation-based Performance Study

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***Abstract*—The integration of automotive communications in 5G systems must build on a clear understanding of the performance of services for connected vehicles in today's LTE deployments. In this paper, we carry out a simulation-based performance evaluation of automotive communications in LTE, with particular attention to realism: to that end, we investigate the impact of different road traffic models, employ a state-of-the-art commercial LTE tool, and study a practical service use case. Our results demonstrate that unrealistic road traffic datasets can bias network simulations in urban vehicular environments, and provide insights on the limitations of the current radio access architecture, when confronted to connected vehicles.**

I. Introduction

Automotive communications are commonly considered as enablers of a wide range of new and compelling telecommunication services, and are one of the main use cases in the design of future 5G networks. In order to meet the expectations, automotive communications must be efficient (e.g., in terms of end-to-end latency), reliable (e.g., in terms of coverage), and operate at scale (e.g., accommodate a 100% penetration rate of the technology). As a result, they raise a number of technical challenges. Data flows initiated by vehicles (i.e., by the driver, passengers, or vehicle itself) may endure several kilometers, stressing the network mobility management functions with frequent and numerous handovers. In addition, pervasive operations such as *cooperative awareness* [1] and *decentralized environmental notification* [2], originally standardized for dedicated short range communications (DSRC), may soon be moved to the 5G cellular ecosystem [3], inducing significant additional load on the radio access infrastructure. Finally, how to benefit from novel concepts introduced in 5G [4], such as *network slicing* or the pervasive application of *network softwarization*, remains an open question in the context of vehicular communications.

Understanding the performance of connected vehicles in presence of the current LTE deployments is a much-needed preliminary step towards an informed dimensioning of the 5G cellular access infrastructure, and a sensible design of algorithms that allow for an optimized operation of future 5G networks. However, the literature on this subject is thin. Previous studies have shown that LTE will hardly be able to accommodate the traffic generated by cooperative awareness applications [5], and solutions have been proposed that rely on message filtering [6] or take advantage of the MBMS functionality [7]. Similar considerations also hold for floating car data management. studied for instance in [8].

In this work, we contribute to investigations of the limitations and drawbacks of the LTE-A architecture when confronted to automotive communications, from two perspectives.

(i) We carry out simulations that reproduce automotive communications in LTE at an unprecedented level of realism and detail. Specifically, we consider multiple models of road traffic that feature varied degrees of realism at macroscopic and microscopic levels. Such models are fed to an LTE emulator that models the complete protocol stack, including resource block scheduling, modulation, and coding scheme selection. As these operations are performed in tight interaction with channel quality assessments, we carefully model signal propagation, via ray-tracing techniques. Overall, our simulation setup, presented in Sec. II is a significant step forward with respect to previous works, which rely on analytical models or simplistic network simulations.

(ii) We investigate the impact that different urban mobility models have on association statistics to the cellular network. Our results, presented in Sec. III, show that urban road traffic datasets that are unrealistic at any level can affect the reliability of network simulations. This lets us answer the question of which level of vehicular mobility accuracy is actually *needed* for network simulation: apart from recent work considering highway environments [9], this is an open point to date.

(iii) We study the performance of LTE in a practical automotive service scenario, via the realistic high-detail simulation environment above. Our results, in Sec. IV, provide useful insights on the limitations of the current radio access architecture, when it is confronted to connected vehicles. The significant level of accuracy allows drawing novel guidelines for the design of 5G systems that can meet the requirements of upcoming *automotive verticals*. These observations are expounded in Sec. V, which concludes the paper.

II. Simulation environment

Our simulation environment accounts for heterogeneous models of road traffic, presented in Sec. II-A, and an accurate representation of the LTE network, in Sec. II-B.

A. Urban road traffic models

The rationale for our selection of models of urban vehicular mobility is as follows. We consider the three main components that contribute to the definition of a holistic vehicular mobility model, i.e., road infrastructure, microscopic-level driver behavior and macroscopic-level traffic flows, and alternately reduce their level of realism. This leads to the datasets detailed next.

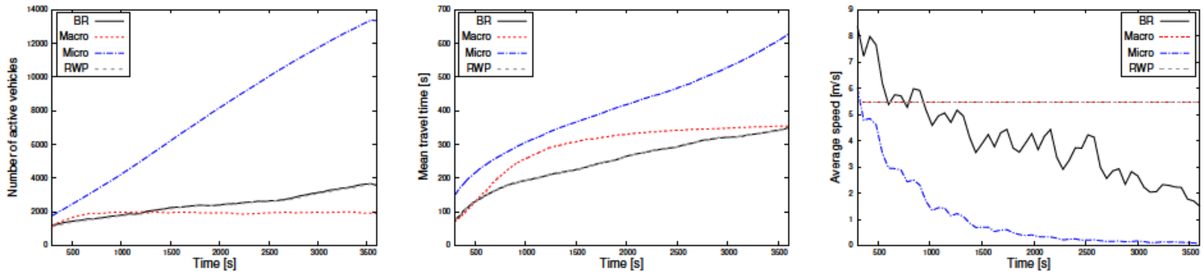


Fig. 1: Main features of the road traffic datasets, as time series. (a) Traveling vehicles. (b) Mean travel time. (c) Mean speed.

Bologna dataset. Our reference dataset is named `Bologna Ringway` (`BR`), a vehicular mobility trace originally presented in [12], realistic and publicly available[1]. The `BR` dataset leverages road network information extracted from OpenStreetMap[2], by means of an aptly modified version of the `netconvert` tool[3]. The microscopic-level mobility is modeled through SUMO[4], i.e. the current state-of-the-art open-source tool for the generation of vehicular mobility scenarios. Traffic flows are described as a combination of an origin-destination (O-D) matrix that captures the time and start/end locations of vehicular trips, and a traffic assignment algorithm that translates the O-D matrix into complete routes. Specifically, the O-D matrix is obtained from the EU iTetris project [10], and Gawron's dynamic user equilibrium algorithm [11] is employed for traffic assignment.

Overall, the `BR` dataset describes one hour of road traffic during the morning rush hour, from 8 am to 9 am, in a typical working day in Bologna, a middle sized city in the north of Italy. More than 22,000 vehicles travel in the city during the simulated timespan. The dataset was validated using innovative techniques based on publicly available travel time data. A complete discussion of the generation and validation of the Bologna dataset is available in [12].

Macroscopic mobility dataset. This is a simplified version of the `BR` dataset, where the road network and macroscopic traffic flows are preserved, but the microscopic-level model of SUMO is replaced with a naive constant-speed model. The speed of each vehicle is extracted from a Gaussian distribution with mean 5.485 m/s and standard deviation 0.5485 m/s. These values are calibrated on the speed recorded in the `BR` dataset, with the mean matching that in the realistic data, and the standard deviation set to 10% of such value. This parametrization follows common practices in the literature [13].

Hence, the dataset features vehicles that do not interact with each other, e.g., by maintaining safety distance, or with the road signalization, e.g., by stopping at crossing lights. In the following, we will name the dataset `Macro`, since it only preserves macroscopic-level realism.

Microscopic mobility dataset. The second reduced model of the `BR` dataset features realistic road network and microscopic mobility. However, traffic flows are modeled with a simplistic pseudo-random trip model. Specifically, the model considers the same volume of injected vehicles observed in the `BR` dataset, but it assigns origins and destinations proportionally to the capacity of the road segments.

[1]http://www.cs.unibo.it/projects/bolognaringway/

[2]OpenStreetMap, http://www.openstreetmap.org

[3]Netconvert tool, http://sumo.dlr.de/wiki/NETCONVERT

[4]Simulation of Urban MObility, http://sumo.sourceforge.net

Parameter	Value
Center Frequency	2 GHz
Bandwidth	10 MHz
Fast Fading Model	Urban Macro (UMa)
eNodeB Tx Power	43 dBm
eNodeB Height	25 m
Scheduler	Proportional Fair
Pathloss Model	WINNER+

TABLE I: LTE simulation parameters.

The dataset, named `Micro`, is representative of a very popular approach to mobility modeling in the vehicular networking literature. As O-D matrices are hard to retrieve, researchers often rely on realistic road maps and microscopic mobility, but then assign traffic in a pseudo-random fashion.

Random mobility dataset. As a baseline dataset that does not even consider the road infrastructure, and is fully random, we consider the well-known random waypoint model, denoting it as `RWP`. The model assumes that a vehicle i at position p_i uniformly chooses a next destination p_{i+1} inside the simulation area, and then reaches it with a randomly chosen speed s_i. In our case, s_i is a random variable whose distribution follows that derived for the speed in the `Macro` dataset. No pause time is considered between subsequent movements. Each vehicle starts and terminates its journey at the same time as in the `BR` dataset.

Fig. 1 summarizes the main features of the vehicular mobility datasets. Fig. 1(a) shows the time series of the number of vehicles that travel concurrently in each dataset. The `Micro` dataset yields a much denser traffic compared to the other scenarios. Despite the volume of injected vehicles being the same across all datasets, unrealistic macroscopic traffic flows rapidly congest a road network tailored for the actual travel demand. The `Macro` model lets vehicles travel more smoothly due to the total absence of driving constraints, resulting in a reduced traffic when compared to a realistic situation. Finally, `RWP` overlaps with `BR`, since start and end time of trips in the former are calibrated to match those in the latter.

Fig. 1(b) and Fig. 1(c) portray the mean travel time and average vehicle speed. The travel time is the highest and the speed is the lowest in the `Micro` dataset, due to significant road traffic congestion. For both `RWP` and `Macro`, the average speed is constant, due to the random nature of their microscopic mobility. Concerning the mean travel time, the `Macro` model overestimates it, whereas `RWP` overlaps with `BR`, since the number of running vehicles is tuned to match.

B. LTE emulation environment

The system-level LTE simulator we employ is developed by Nomor Research GmbH[5]. This is a multi-cell, multi-user LTE-Advanced emulator with real-time simulation capabilities. The tool incorporates a complete LTE protocol stack model for the user plane, where protocol functionalities have been limited to the main ones in order to enable real-time performance. The tool features a full-fledged, accurate Medium Access Control (MAC) layer, and the physical (PHY) layer is emulated by leveraging off-line link-level simulation results. This approach allows taking into proper account the channel estimation, channel coding, modulation schemes, and receiver equalization. The simulator runs at Transmission Time Interval (TTI) level granularity along time, and at Physical Resource Block (PRB) level along the frequency axis. This makes the simulations accurate and detailed enough to produce realistic results for subsequent fine-grained analysis: for the sake of clarity, the degree of output detail is similar to that enabled by a traditional network protocol analyzer such as Wireshark.

We consider eNodeBs in the target scenarios to operate at a 2GHz center frequency, with 10-MHz system bandwidth, and TTI=1 ms. The radio conditions are modeled according to detailed statistical and physical models, with the aim to generate realistic results. For the simulations presented in this paper, we relied on WINNER+ channel models [14]. The effect of buildings on received signal strength is modeled by considering whether there exists a direct Line-of-Sight (LoS) link between the eNodeB and the user, or if the link is shadowed because of the presence of buildings, i.e. Non-Line-of-Sight (NLoS) signal propagation. The radio propagation models consider different pathloss as well as fast fading for LoS and NLoS cases. The simulations also consider inter-cell interference from surrounding antennas, as well as background traffic induced by non-vehicular users. The latter is recreated using traffic generators based on 3GPP standards for LTE network. The key simulation parameters are outlined in Tab. I.

The real-world deployment of the LTE infrastructure in the Bologna region is inferred from OpenCellID[6], a crowdsourced database of base stations locations worldwide. eNodeBs are identified by their cell identifier (CID) and Location Area code (LAC), and their position is triangulated using measurements provided by contributing users. To filter out incorrect information that is known to affect OpenCellID data [15]: *(i)* we mark as noise eNodeBs with less than two measurements, for which no triangulation is possible; *(ii)* we cluster eNodeBs of a same mobile operator using a dutifully parametrized[7] DBSCAN algorithm [16], and map the center of mass of each cluster to a single eNodeB. The resulting deployment is shown in Fig. 2, where the eNodeB are distinguished on a per-operator basis. We remark a concentration of eNodeBs along the railway track and around the railway station (thin red ellipse), as well as along the main downtown streets. The allocation of vehicular users to different mobile network operators is performed by accounting for the actual market shares in Tab. II, obtained from the annual report of AGCOM, the Italian authority for warranties in communications [17].

[5]http://www.nomor.de

[6]http://opencellid.org/

[7]After extensive tests, we set MinPts=2 and ϵ=0.001.

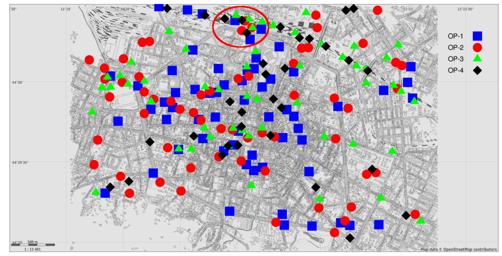


Fig. 2: Deployment of eNodeBs in the Bologna urban area.

Operator	OP-1	OP-2	OP-3	OP-4
Share	34.43%	32.15%	23.15%	10.27%

TABLE II: Market shares of Italian mobile network operators.

III. Road traffic and network simulation

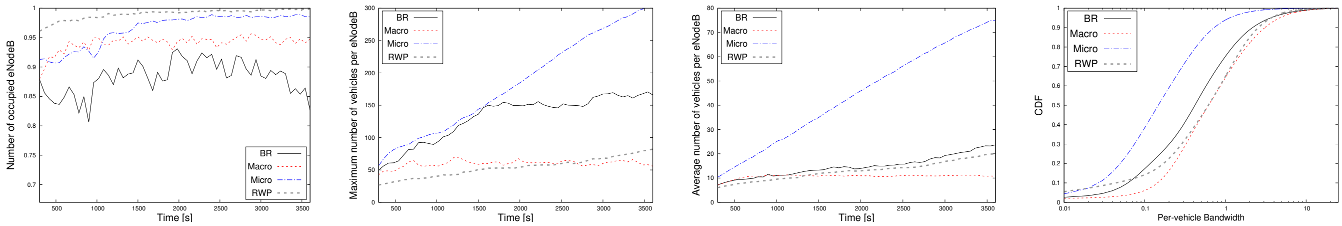
We investigate how the different mobility models presented in Sec. II-A affect the LTE network simulation. Our evaluation is application-independent: therefore, we do not consider one precise service for connected vehicles; rather, we study the impact that the mobility models have on general association statistics between vehicles and cellular base stations.

Since we are interested in basic association statistics, a detailed system-level simulation such as the one described in Sec II-B is unnecessary at this stage. Instead, we employ a signal-strength stochastic simulator that can scale up to a large scenario such as `BR`. At each simulation step, which we set to 1 s, vehicles are attached to the best eNodeB in terms of Signal-to-Noise Ratio (SNR). This assignment is computed after the ray-tracing modelling among all the vehicles-eNodeB pairs of a given operator (using the building shape data included in the `BR` dataset package), and the application of the Path Loss model for Macro Urban scenarios (UMa) outlined in the ITU-R technical report [18].

The average height of the buildings is 15 meters, while the eNodeB antennas are placed at 40 meters [18]. Finally, we use the SNR to compute an estimate of the downlink communication bandwidth available to vehicles, via the empirical LTE model proposed in [19]. As such model does not account for the number of user equipments concurrently served by an eNodeB, we approximate the instantaneous rate of each vehicle by dividing the total eNodeB bandwidth by the number of vehicles the eNodeB is serving at that time.

Fig. 3 summarizes the cellular connectivity results obtained with each vehicular mobility dataset. The plots refer to one operator, as we obtained consistent results across all operators, omitted due to space limitations. All results are shown as time series: traffic conditions are not homogeneous over time in Fig. 1, and time series let us appreciate how such variability affects the network connectivity statistics. In each plot, four curves represent the performance recorded under the different mobility datasets: the dissimilarities among the curves are evident in all cases, and highlight *the strong bias that different representation of road traffic can induce in the network simulation*.

Specifically, Fig. 3(a) shows the fraction of active eNodeBs, i.e., eNodeBs that serve at least one connected vehicle. We discussed in Sec. II-A how the unrealistic travel demand of the `Micro` dataset induces a large congestion: being spread uniformly over the road layout, such congestion leads to a



(a) OP-1. Active eNodeBs. (b) OP-1. Max eNodeB associations. (c) OP-1. Mean eNodeB associations. (d) OP-1. eNodeB-to-vehicle SNR.

Fig. 3: Vehicular access statistics in Bologna, for operator OP1. The curves in each plot map to diverse mobility datasets.

higher number of active eNodeB. In the `Macro` case, the average speed is constant, hence the vehicles tend to be slower than those in the `BR` dataset, especially in the first part of the simulation: at that time, the longer travel times lead to a larger fraction of active eNodeBs in `Macro` than in `BR`. When the `RWP` dataset is employed to represent the road traffic, vehicles are spread all around the map, and establish associations to an unrealistically high number of eNodeBs. In summary, *any reduction of realism – at the macroscopic or microscopic level – causes an artificially even distribution of associations over the geographical area.*

Fig. 3(b) displays the maximum number of connected vehicles served by a single eNodeB. The number of vehicles that concurrently travel in the urban scenario clearly affects this metric, as evidenced by the opposite behaviors in the `Micro` and `Macro` cases. That number is identical by construction in the `RWP` and `BR` datasets: however, the much more uniform distribution of vehicles in the former model leads to maximum association values that are unrealistically low, and close to those of the `Macro` setting. Equivalent trends are observed on the average associations per eNodeB, in Fig. 3(c), even if the scale is reduced in the case of `BR`. These results let us presume that *unrealistic models of the macroscopic and microscopic dynamics of vehicular traffic have opposite effects on the association load, which is overestimated in the first situation and underestimated in the second one.*

To conclude our investigation of connected vehicle access, Fig. 3(d) depicts the Cumulative Distribution Function (CDF) of the downlink communication bandwidth available to vehicles, as measured during the whole simulation. As previously discussed, the bandwidth depends on the SNR received by the eNodeB vehicles are currently associated to, as well as on the association load at that same eNodeB. The sheer number of vehicles in the `Micro` dataset causes congestion not only in the road network, but also at the cellular access, with a dramatic reduction of the per-vehicle capacity with respect to the more realistic `BR` case. Conversely, vehicles in the `Macro` model enjoy an exaggerated capacity, with critical low-bandwidth situations that are basically eliminated from the simulation. The `RWP` dataset leads instead to a heterogeneous CDF, with a significant portion of vehicles that are out of network coverage (zero bandwidth). In conclusion, the same trends observed for the association load also apply here: once more, *any deviation from a realistic mobility modeling leads to strong biases in terms of the downlink communication bandwidth offered to connected vehicles*, with repercussions on the performance evaluation of services or protocols.

In the light of these results, the fully realistic `BR` dataset is actually *needed* for a dependable simulation of vehicular access in LTE. Hence, we discard the other models, and feed the `BR` dataset to our high-detail system-level simulations.

IV. Simulating an automotive service in LTE

We consider a practical service use case, in Sec. IV-A, and run accurate simulations using the state-of-the-art emulator presented in Sec. II-B. Results are discussed in Sec. IV-B.

A. Automotive service and KPIs

Our reference application is a collision warning service that lets connected vehicles warn each other about dangers they detect. The service runs on all vehicles, and is triggered by a vicinity-based hazard-detection algorithm. Specifically, as vehicles move along city roads, they may have to suddenly decelerate due to unanticipated congestion, hurried pedestrian crossings, or sharp turns by cars in front. To avoid collisions in these situations, the cooperative warning system forces vehicles to announce hard braking to all vehicles nearby.

The collision warning service requires car-to-car communication, which is implemented through LTE. Thus, connected vehicles send and receive warning notification via the mediation of eNodeBs. Warning messages are small packets (2 KB in our simulations) designed for minimum latency, generated by the vehicle detecting the hazard, and transmitted to the serving eNodeB in the uplink direction. The eNodeB then forwards these packets in downlink to target cars, selected depending on the scope of the notification.

The two most sensible Key Performance Indicators (KPIs) in the context of such an automotive service are the throughput and the end-to-end delay experienced by connected vehicles. The user throughput is the data rate observed at the user's Packet Data Convergence Protocol (PDCP) layer, after packet loss, retransmissions and link adaptation. In our warning notification system, many vehicles may send warning messages at the same time to the same eNodeB causing congestion, due to a limited number of resources, which becomes worse for vehicles with bad channel conditions. The throughput KPI is also a good indicator for such cases, besides serving as a standard measure for network quality. The end-to-end delay represents the total time needed for a message to be transferred from warning source vehicle to a recipient car over the infrastructure. This time includes LTE inherent extra delay for scheduling, uplink grant access, Hybrid Automatic Repeat Request (HARQ) and processing/decoding delays.

The collisions warning service is simulated in a representative neighborhood of Bologna, depicted in Fig. 5(a). The selected area is a representative portion of the Bologna covers 0.6 km^2 characterized by a significant presence of all mobile

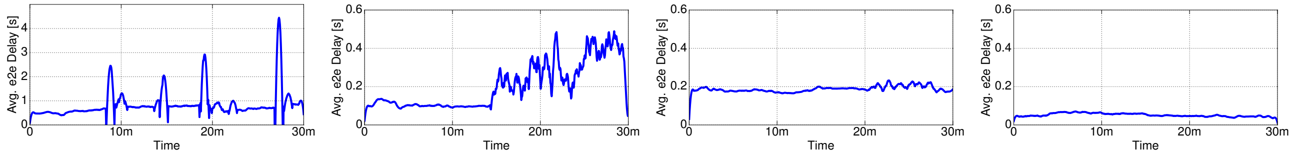


Fig. 4: End-to-end delay at four representative eNodeBs, over time. Average delays are 0.84, 0.22, 0.18 and 0.05 s, respectively.

network operators. It also encompasses important landmarks of the city such as the railway station and main bus terminal.

B. Results and insights

Our choice of LTE-based automotive service, jointly with the degree of realism and detail of the simulation, prove especially useful to understand the limitations of the current radio access technology with respect to applications for connected vehicles. This is true at different levels, and we organize our discussion of results by separating network design issues.

Resource deployment. As also mentioned in Sec. III, the actual performance of the cellular network depend very much on the planning of the radio access infrastructure, when superposed to the movement patterns of terminals. This is particularly true for automotive services, where connected vehicles often cluster in crowded, yet predictable, platoons. Elements like intersections, traffic lights or roundabouts introduce perturbations on the vehicular movements that cause two negative effects on the infrastructure: *(i)* connected vehicles attach to eNodeBs in a very uneven manner, causing oversubscription at certain locations, and *(ii)* dedicated applications like the one we evaluate in this paper generate a high volume of data traffic, since inter-vehicle distances are reduced and collisions are more likely to happen.

We evaluate this problem by measuring the load, in terms of average end-to-end delay, of each eNodeB. Results are shown in Fig. 4, for four representative eNodeBs. Clearly, the physical placement of an eNodeB plays a fundamental role in determining its performance. Several eNodeBs are overloaded at times, generating spikes in the end-to-end delay and a higher average latency in general. Other eNodeBs experience very low load from connected vehicles, hence they can guarantee a very low latency. By looking at where the high-load eNodeBs are located in Fig. 5(a), we observe that they serve the area close to the Bologna bus terminal, which is also in proximity of a very busy crossroad. There, slow traffic and stop-and-go patterns induce a very high load on the infrastructure, with a much degraded latency performance when compared to that of the less loaded eNodeBs.

Based on such results, we stress how *understanding vehicular movement patterns to deploy network resources will be critical in 5G networks*. Even more so, when considering the introduction of paradigms such as Network Function Virtualization (NFV) and Software Defined Networking (SDN), which will allow a dynamic assignment of resources. The latter shall be reallocated according to the road traffic dynamics, substantially improving the network performance. In particular, *on-demand* and anticipated provisioning of resources becomes foreseeable when considering the regularity of road traffic.

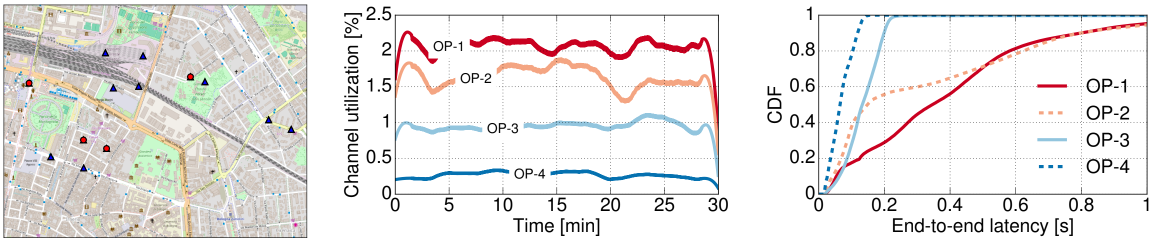
Although the design and validation of such optimized resource orchestration algorithms is out of the scope of this paper, our work demonstrates and quantifies for the first time the existence of the problem, and is thus a preliminary step towards automotive-aware resource orchestration algorithms for virtualized mobile networks.

Optimized resource usage. Automotive services usually rely on frequent transmissions of very small packets. However, LTE is designed for long-lasting data flows accommodated into continued sessions: in fact, *all the control messages needed for the correct setup of a Data Radio Bearer (DRB) are an unnecessary burden for the network infrastructure, if frequent and connectionless packets need to be exchanged*. This not only limits the number of devices that may be connected to the network (as state has to be maintained for each attached user equipment), but it reduces the performance of the served end users. This problem, which is common to all machine type communications (MTC), is exacerbated by the high mobility of vehicles that will rely on an automotive network slice.

A related problem is the waste of network resources caused by the small packet length. Common LTE MAC schedulers adopts strategies like Proportional Fairness or Round Robin that aim at maximizing the long-term transfer rate of user equipments. In an automotive service environment, such a long-term service rate may not be the correct goal to target. This calls for *the implementation of automotive-aware schedulers that are capable of optimizing the relevant KPIs for vehicular communications*. Service-aware scheduling allows for a better utilization of Physical Resource Blocks (PRB) that are easily misused when assigned to flows using the legacy LTE QoS framework.

These situations are reflected in our high-detail simulation, as shown in Fig. 5(b). The plot shows the actual share of the available bandwidth used by each operator during the whole simulation. The available bandwidth is calculated by means of the Shannon theorem, $C = B \log(1 + S)$, where C is the capacity limit, B the channel bandwidth (10 MHz in this case) and S the SNR perceived by each connected vehicle. The used capacity, instead, is the actual amount of data exchanged at PDCP level. All values are averaged over all the user equipments at every second. Although the real PRB utilization pattern depends on the decisions taken by the scheduler at superframe level, the trend shown in Fig. 5(b) helps us understanding how a proportional fair (PF) scheduler may fail to share the available spectrum with other types of telecommunication services. Hence, the sharing of resources among heterogeneous services that use the same infrastructure (e.g., enhanced Mobile Broadband) shall be jointly optimized for all services, including the automotive one.

Automotive KPIs awareness. Among all the envisioned 5G telecommunication services, automotive communications impose the most stringent requirement in terms of latency. This is understandable, when considering the the end-to-end delay required for applications like collision avoidance or for any other kind of cooperative awareness system where reaction



(a) (b) (c)

Fig. 5: (a) Loaded (red circles) and unloaded (blue triangles) eNodeBs. (b) Channel utilization. (c) End-to-end latency.

is needed in a very short time. Although there is not a fixed value for the maximum latency requirements, it is expected that for many applications (e.g., traffic signal violation or left-turn assist) the maximum bound is 100 ms, while for others such as pre-crash sensing this limit goes down to 20 ms.

Low latency is not the main focus of LTE, which was historically designed to support high bandwidth communications, so it is expected that such a tight latency requirement will not be met without any modification in the stack. In this context, our simulations demonstrate how far the current technology is from fulfilling the KPIs needed by automotive service deployed at scale.

Fig. 5(c) depicts the end-to-end latency experienced by messages generated by our hazard warning application. Clearly, the current LTE architecture falls short of meeting even the most relaxed latency requirement. No operator in our scenario can guarantee a significant probability of vehicle-to-vehicle communications below, e.g., 100 ms. In fact, the operators serving the largest market shares incur in very high delays well beyond 200 ms for the vast majority of the connected vehicles they serve. Although many factors concur in determining such a high latency, our simulations highlight those that play major roles. Specifically, *(i)* the time needed to set up data radio bearers for all the UEs in the network, *(ii)* the queuing delay at PDCP, and *(iii)* retransmissions. Therefore specific techniques, capable of mapping vehicular data traffic to the most appropriate vehicular aware network functions (e.g., lightweight signaling procedures for vehicular UEs) are needed to correctly support vehicular traffic in future 5G networks.

V. Conclusions

In this paper, we investigated the automotive service support provided by the current LTE architecture. We adopted a realistic simulation approach that allowed unveiling the critical impact of dependable mobility modeling. Our results demonstrate that LTE networks have significant limitations when faced to pervasive services by automotive verticals. They also let us derive useful guidelines for the design of future 5G networks: *(i)* the deployment of the infrastructure and the orchestration of resources must take advantage of the predictability of traffic flows; *(ii)* the control those same resources must occur in service-aware fashion, e.g., at the scheduler level; *(iii)* new mechanisms or network functions must be developed that are specific to automotive applications.

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