Towards AI-Native Vehicular Communications

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***Abstract*—The role of fast yet reliable wireless communications in various application domains is getting ever more important. At the same time, as use cases are becoming more and more complex, application requirements are getting ever more stringent. One example is intelligent transportation, where the efficiency and reliability of wireless data delivery is essential for effective service support. As a consequence, in this context the adoption of AI techniques is widely considered crucial for enabling vehicular communications to adapt to dynamic changes of the environment. In this position paper, we discuss some representative applications of advanced AI tools in vehicular communications. In particular, we elaborate on the potential of distributed learning based on federated learning, of proactive service provisioning, and of graph neural network for enabling AI-native vehicular communications.**

***Index Terms*—ITS, V2X communications, ML/AI, distributed learning, QoS-prediction**

I. Introduction

The emergence of new, data-intensive intelligent transportation systems and services with tight QoS constraints and complex (and potentially conflicting) requirements is poised to push current vehicular communication (VC) paradigms to their limits [1]. Applications such as remote and autonomous driving, holographic driver vision for situation awareness [2], real-time intelligent traffic scheduling [3], and personalized, interactive infotainment based on tactile vehicular communications [4] bring new and complex combinations of QoS requirements which challenge current paradigms for vehicular communications, and which even 5G is not able to satisfy adequately. To cope with such a tendency towards ever demanding applications and services, AI-based mechanisms are progressively permeating all aspects of vehicular networking. V2X communications are thus poised to transition towards the ”AI-native” paradigm which already permeates wireless communications. That is, in a set of technologies where learning-based mechanism play a foundational role, enabling context-aware vehicular communications in which every node continuously learns and adapts to a dynamic and ever changing environments. This evolution is fostered by the shift from centralized computing to distributed edge intelligence, and by the ever increasing amount of data collected by user devices, by vehicles, in ITS systems and in any part of the wireless network infrastructure. It holds the promise to enable smart resource management, access control, and multi-technology wireless communications with unprecedented levels of efficiency, reliability and flexibility.

Several are the technical challenges which need to be addressed to enable AI-native VCs. Among these a central role is played by the high heterogeneity of vehicular networks, in terms of resource availability and application requirements, which puts to a strain currently centralized learning approaches. Moreover, their dynamicity and volatility, which implies a high churn in the set of distributed communication resources, poses a serious challenge to mechanisms for dynamic coordination, for resource pooling and sharing, and ultimately to the possibility of guaranteeing tight QoS levels for computing and communication services.

This position paper is about a set of learning-based enablers which are poised to play a pivotal role in overcoming these challenges, and in satisfying the following requirements:

- need to learn at the edge, in spite of dynamicity, for scalability, resource efficiency and better privacy protection;
- need to satisfy a very heterogeneous set of QoS requirements, some very stringent, in dynamic settings;
- need for robust and high availability multihop connections.

The paper is structured as follows. In Section II, we investigate the importance of distributed (federated) learning for V2X applications. Section III deals with proactive quality-of-service provisioning in vehicular networks, whereas Section IV discusses the use of a real time emulation platform (EMANE) and the application of graph neural networks for V2V. Section V concludes the works.

II. Distributed Learning Frameworks for V2X

Recently, distributed learning architectures have received considerable attention from the research community [5]–[12], as they promise to overcome some of the main limitations of centralized approaches, such as limited scalability and communication bottlenecks.

A. Why Distributed Learning in V2X?

Distributed learning schemes find in V2X scenarios a natural application. Firstly, in collaborative tasks such as autonomous coordinated driving [13], [14] and platooning, the direct sharing with other vehicles of raw data collected locally by each vehicle might easily overload the communication infrastructure, challenging the effective support of critical tasks and services. Therefore, distributed learning, where only the results of the learning process are shared among vehicles, may help in alleviating the communication burden. Secondly, distributed learning does not require a powerful central computing node, thus facilitating its implementation in V2X scenarios. Thirdly, the power consumption of learning tasks is likely to be trivial compared to the total power consumption of vehicles. Therefore, we can assume vehicles are able to provide steady and considerable computing capacity for distributed learning.

In addition, tasks such as object detection [15] and steering angle prediction [16] benefit from knowledge sharing among all participating vehicles. Since the data collected by vehicles are likely to be limited locally and biased, the sharing of the learned knowledge may contribute to the elaboration of some form of local consensus among vehicles in a given scenario, thus potentially improving the vehicle's awareness of the surrounding environment and the driving decisions. Moreover, sharing machine learning models instead of data offers better support to privacy protection, as raw data (possibly containing sensitive user's information) is not shared [17].

B. System Structure for Federated Learning in V2X

A distributed learning approach which is suitable for the above mentioned applications is federated learning (FL) [18], in which the participating workers (vehicles) share a same learning task, and thus a same machine learning model. The data for training the model is often collected locally by the vehicles. After some local training, workers in FL share their trained model with others and/or with a parameter server, and the knowledge learned locally is thus propagated to all participants. Based on the existence of a central parameter server, FL can be classified into centralized [18] and decentralized [19]. Centralized FL requires a relatively stable communication connection between the server and the workers, for the learned model to propagate effectively and improve over time. On the other hand, decentralized FL only requires reliable device-device communications between workers. The efficiency of information propagation thus depends on the structure of the connectivity graph of workers [20]. For V2X applications, centralized FL is suitable for a scenario with a server, either predefined or elected from workers. Decentralized FL instead can be applied to spontaneous learning tasks in a server-less region. There are also schemes which are a combination of the two approaches mentioned above, normally with a hierarchical structure [21], [22]. For instance, in a two-layer hierarchical system, several edge servers coordinate the workers within a specific sub-region, acting as a parameter server for only a subset of the workers. The communication between edge servers is then performed with or without a central server. Hierarchical FL systems are also suitable for V2X scenarios when there are edge nodes interconnected as sub-servers.

C. Challenges of Federated Learning in V2X

The learning schemes described still face significant challenges when deployed in realistic V2X scenarios. The most prominent limitation is the volatility of the wireless channel (and the churn in the set of workers) resulting from the mobility of vehicles. For FL, various solutions have been proposed in different synchronization algorithm to address this limitation [23].

For synchronous FL, where there is a specific round time for workers to train and upload models, the goal is to have a set of participating workers with similar overall training plus uploading time. Here, the tradeoff is between allowing more participants in the scheme, and minimizing the idle time for each worker (i.e. the time spent waiting for other workers to complete their local training step). To this end, it is possible for the server to perform client selection [24] in each round, choosing workers capable of training and uploading within certain time limits. Another solution from the server's perspective is to optimize the allocation of communication resources as in [25], [26]. In V2X applications, the server needs to know the computing capacity and link conditions of each worker, which is not always feasible in practical scenarios. Other solutions entail work from the clients' side. Under a known time limitations, workers either speed up local training by allocating more computing resources or training models partially [27] with gradient sparsification [28], or reduce the communication time by compressing the model [29]. Such methods do not apply in those conditions in which vehicles completely lose the connection with the server.

For asynchronous FL, where the server / workers performs model aggregation upon receiving a model update, the variability in communication time due to vehicles' mobility can also be problematic. Although the server / workers are open to accept model updates of any training and uploading duration, model uploaded by vehicles with bad communication conditions are likely to be based on an earlier distributed global model. These model updates are conventionally referred to as stale, which could be harmful to the global model because they are either less trained or biased towards a specific worker. The research community offers limited solutions for this phenomenon, usually with a attenuation function to decrease the weight of stale model updates during aggregation. In general, such solution leans more on decreasing the negative impact of stale models from slow workers. For incorporating the contributions from possibly out-of-synchronous vehicles in V2X, there needs to be dynamic training and uploading strategy from clients' side so that their computational results are received in a timely manner.

III. Learning-based proactive strategies for QoS provisioning

Several V2X use cases, such as tele-operated driving, vehicle platooning, and high-definition map collecting and sharing, put stringent QoS requirements in terms of coverage, data rate, delay, and other related Key Performance Indicators (KPIs) [30]. To avoid any service interruption, these requirements need to be always satisfied despite the challenging and highly variable conditions experienced in vehicular environments. In these use cases, changes in vehicle and/or application behaviors may have a strong impact on the service performance. For example, a tele-operated vehicle that is performing a turn may generate a higher video bit rate due to changes of background images and change of camera focus while turning. Thus, a change of vehicle behaviour (e.g., left turn) will have an immediate impact on application behaviour (e.g., increased bit rate). On the other hand, a reduction of video resolution by the application to accommodate a reduced network capacity could result in speed reduction, because the video quality might not be enough to safely keep the current speed.

In this regard, predictive QoS (PQoS) schemes might help towards ensuring seamless operations by forecasting any potential QoS degradation, and adapting the system behavior in a proactive manner. This approach guarantees that appropriate QoS performance, especially for time-critical applications, are always met, even in presence of challenging network conditions. By continuously predicting QoS performance, mobile networks may inform V2X applications through In-advance QoS Notification (IQN) in case a service degradation is foreseen [31]. Upon the reception of a IQN, applications can proactively adapt their behavior in such a way to limit the impact on the service experience and avoid any service interruption.

The prediction algorithm is one of the main components of PQoS schemes, since forecasting QoS performance with high accuracy is essential for the proper functioning of this solution and, to this aim, AI-based algorithms represent a key enabler. Indeed, compared to traditional statistical approaches, such as parametric models, AI-based approaches possess better generalization properties and they are able to achieve high accuracy if properly trained. This approach is made possible by the pervasiveness of ML-based intelligence on vehicles, as well as by the growing amount of data collected by and about moving users. Research in this context spans over several dimensions, but is still at a rather early stage. In the following, we briefly review the main ones.

A. Architectural enhancements for Predictive QoS

This dimension concerns the design of architectural frameworks and signaling schemes that can enable the actual delivery of IQNs to the connected vehicles. These frameworks mainly attempt to address three questions: how to monitor and collect data, how to make predictions, and how to deliver predictions to the interested parties. 5G already support PQoS functionalities as part of the NWDAF [32]. This function provides the "Notification on QoS Sustainability Analytics" service, which monitors QoS performance of subscribed applications and notifies the application server in case the requirements cannot be satisfied [32]. Other solutions have been proposed in the literature. For example, [33] proposes a new entity for the radio access network able to collect data from different sources, to make QoS predictions based on the acquired data, and to apply network countermeasures in case of QoS degradation. These solutions represents a first attempt to include the PQoS functionalities in mobile networks. However, the distributed and highly dynamic nature of V2X use cases makes accurate QoS predictions difficult to achieve. In this regard, new frameworks that are tailored to the peculiar characteristics of vehicular scenarios need to be investigated.

B. Measurement campaigns and datasets

Currently, the availability of datasets that can be used as an input to train and test QoS prediction algorithms is very limited. Moreover, the lack of datasets that can be used as a common reference prevents the fair comparison of different proposals. In this regard, different initiatives are trying to overcome this challenge. For instance, measurements of data rates for high-mobility users have been conducted in [34] and [35]. Also, the authors in [36] presented an open-source dataset that was collected from a prototyped 5G system, and used it to assess the performance of different algorithms for uplink throughput prediction. Such campaigns are deemed important though, as they capture the unique and complex characteristics of the radio environment under study. Measurement parameters of interest may contain data from base stations, core network, weather and traffic-related databases, to name a few, and may apply to multiple mobility and topology scenarios.

C. Algorithms for QoS predictions

Perhaps the majority of the state-of-the-art focuses on this issue (e.g., [37], [38]). Research works in this context present a) a QoS prediction approach (e.g., a QoS prediction mechanism that uses an LSTM architecture) and network-related QoS metrics, in order to identify specific patterns and predict in advance the QoS that will be available in the near future to Connected Autonomous Vehicles (CAV) [38]), b) a proposed method for the data collection (simulation/emulation/real traces), c) the features of the collected/available dataset, d) the ML algorithms deployed, e) the evaluation KPIs considered, and f) the setup that has been used in terms of hardware, software, network, etc.

D. Testbeds and simulation platforms

The design of efficient PQoS solutions is challenging, as it requires to perform multiple rounds of training and optimization which are hard to carry out in real networks because of high complexity, fragility, and costs. In fact, mobile operators typically do not grant access to their networks for research purposes, because the risk of damaging the infrastructure or infringing privacy policies cannot be tolerated.

Experiments with testbeds represent a viable solution to emulate the behavior of real systems with a high level of realism. For example, in [39] the authors presented a testbed built using an RC car equipped with a 5G modem, as well as high-resolution cameras and LiDAR sensors. While this approach can achieve a high level of realism, it presents several limitations in terms of scalability, preventing evaluations with a large number of users.

Recently, simulations have emerged as a tool to evaluate the performance of PQoS solutions without the need for real systems to be deployed. In [40], the authors presented a full-stack simulation framework to design and test AI-based PQoS solutions. The framework features accurate models for the simulation of wireless channels and vehicles' mobility, as well as an accurate application model. One of the main advantages of this approach is that it does not require any specialized hardware, thus reducing costs with respect to the above two. Moreover, it allows setting the operating conditions under which the system needs to be evaluated, and to replicate the same conditions in such a way as to compare the performance of different PQoS designs in a fair manner. However, the validity of the results strongly depends on the accuracy of the simulation models, which should be carefully taken into account in order to draw the right conclusions [41].

IV. A USE CASE: APPLICATION OF GNNS TO ROUTING OPTIMIZATION

To illustrate some of the challenges mentioned, this section focuses on improving the performance of mission critical applications using V2V communications without infrastructure support. The context of interest spans the topics of MANET, VANET,3GPP D2D and autonomous vehicles communications. The focus here is on mobile nodes which can directly communicate to each other to form a Mobile Ad-hoc Network using sub-6GHz wireless communications. Each mobile node serves as router to deliver IP packets to nodes beyond their direct neighbors. Due to limited spectrum resources, the number of mobile nodes typically involved is less than about 100: 24 in the case of the well-accepted and realistic mobility scenario for tactical MANET, openly available at anglova.net [42] and presented in Figure 1.

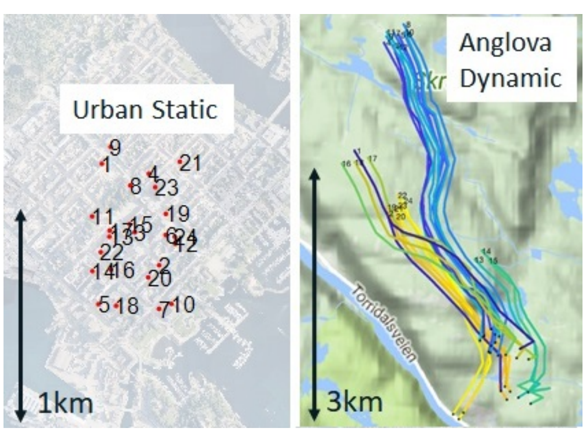

Fig. 1. Illustration of two mobility scenarios. LEFT: an urban static scenario and RIGHT: the dynamic anglova.net scenario: CP1 with 24 nodes. The traces from North to South show the mobility of the nodes.

The communication in V2V networks should offer a large throughput and a high Completion Ratio (CR) in order to provide the user with updated information from all other nodes. In typical MANETs applications, the throughput of the network is low because of the routing nodes and a poor resource allocation scheme. The performance can be increased of the network by considering an adaptive resource allocation method in collaboration with a distributed routing scheme. The traffic data considered here is assumed to be a worse case scenario where each node produce a unicast packet for each of the other nodes. Each packet is acknowledged if correctly received at its destination. The user traffic does not support packet retransmission when a message is lost. Unless stated otherwise, all nodes send messages to all other nodes at random but with the same average bit rate. The performance is defined here mainly as the Completion Ratio (CR), equal to the percentage of correctly acknowledged messages received within a given maximal Round Trip Time (RTT) of 20s.

A. Solutions for V2V multi-hop

Solutions to obtain the best possible performance can be formulated as the combination of three algorithms: a routing scheme, a resource allocation method, here a time scheduler and a flow control process. Fig. 2 presents the interactions between these three algorithms. Without congestion,

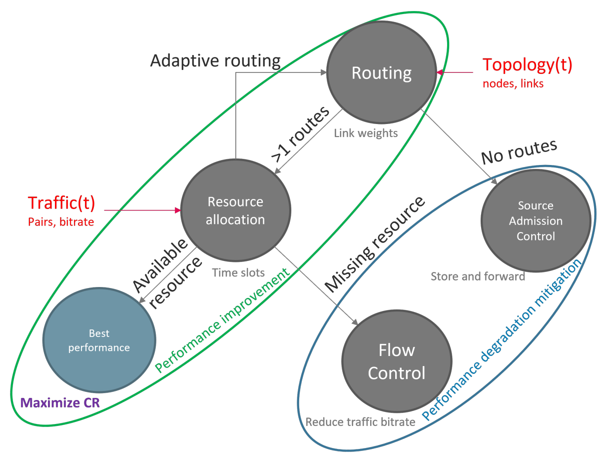

Fig. 2. Illustration of the problem in V2V. The routing is linked to the resource allocation scheme as one cooperative approach to increase the Completion Ratio performance metric in V2V networks. The topology is important for the routing and the traffic for the resource allocation scheme. The Flow control process and Source Admission Control allow to mitigate packet loss due to network breakups or congestion.

the routing protocol is responsible of packet loss if weak quality links are used. The resource allocation is defined as a schedule of time slots specified for a Time Division Multiple Access (TDMA) frame. A poor schedule will congest the nodes because of the large traffic that cannot be satisfied with the current schedule. A flow control mechanism can prevent routing and scheduling problems when the network is disconnected (no route) and/or the resource are limited (traffic ¿ available resource), respectively. As shown in Figure 2, the interaction are multiple and presented from a routing point of view. Optimizing the performance of V2Vs requires routing, scheduling and possibly limiting the transmission rate of sources (Source Admission Control: SAC or Flow Control: FC) or between neighbour nodes (Link Control).

B. Real time emulations: EMANE

Real time emulations are seldom used in the V2V literature due to the complexity of the radio transmissions. The open source EMANE platform, running on powerful Virtual Machines (VMs) using one Linux container per node, renders possible to conduct numerous numerical experimentation close to reality at a fraction of the cost of real measurements.

C. Machine Learning based attempts

Reinforcement Learning (RL) has been investigated to improve the performance of MANETs in real time emulations. Two attempts using GNNs are illustrated in Fig. 3 . The GNN approaches presented in [43], showed the difficulty to convert solutions designed for slowly varying fixed Software Defined Networks (SDN), i.e., a multi-commodity flow problems to a useful schemes for V2V communications.

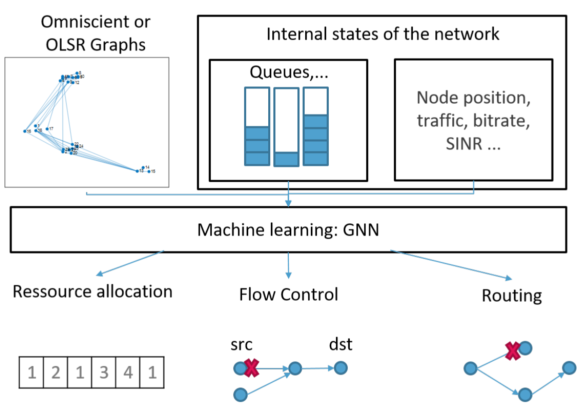

Fig. 3. Illustration of the GNN Model, with the possible inputs or observations: Graph, Queues, position, bitrate, SINR, etc., and possible outputs or action: schedule for resource allocation, link estimation or path prediction for flow control, routing, etc. The goal is to increase the completion ratio and throughput for the admitted source-destination pairs. "Good" policies and rewards remain to be defined.

Currently, the problem still appear to be difficult to solve optimally, even in non-real time and even if an omniscient centralized computing unit existed, due to the time varying demand and topology. Well-know practical solutions do exist such as the Optimized Link State Routing (OLSR) Protocol Version 2 (RFC 7181). A deeper understanding of the main OLSRv2 features (DAT link states, multi-points relay, distributed routing) remains to be exploited. Analysis of so-called OLSR node-view-graphs has recently started.

D. An Omniscient Dijkstra Routing for benchmarking

Repeated emulations confirm that OLSRv2 (Completion Ratio CR=76%) is outperformed by our centralized Omniscient Dijkstra Routing (ODR, CR=94%) [44]. ODR computes all possible shortest paths and then choose a set of single paths to distribute evenly the number of node traversals. When fading is taken into account, we observe that ODR (CR=83%) remains better than OLSRv2 (CR=67%) simply by reducing the ODR pathloss threshold (from 121 to 115dB). But, keeping the ODR pathloss at 115dB worsen the CR (from 53 to 50%) compared to 121dB when weak links are broken such as during the first 300s of the Anglova scenario. The high mobility and the poor connectivity of the network in the beginning of the scenario are claimed to be the major issues. Congestion could also be an issue and remain to be verified. Reducing the time interval of the HELLO packets and Topology Control (TC) benefit OLSR from CR=76% to 82% and OLSR reacts faster to topology changes.

E. A GNN attempt to improve ODR

Alternative routes in presence of an all to all traffic were investigated using the GNN-t algorithm [43]. GNN-t was trained on the Anglova scenario using the number of traversals derived from the shortest paths (using the Dijkstra algorithm). A small random variation were added to the predicted weight to get a unique set of paths. Considering the small number training set (1000s for the Anglova CP1 scenario), our GNN-t presents unexpected large difference of the weights from one prediction to another. Still, GNN-t showed good performance in minimizing the maximal number of hops compared to ODRb. GNN-t is slightly better than ODR (CR_{gnnt}=81% and CR_{odr}=80%). The nodes on alternative routes become also congested and the latency is increased. Further investigations of GNN-t and improving only the routing did not appear promising.

F. Radio Resource Allocation

Providing additional resources (time slots) to the routing nodes is intuitively beneficial. Additional resources in term of time slots have been scheduled for the most traversed nodes as computed from the routing tables. The sub-optimal schedule is oblivious to traffic thus the performance are limited when using our so-called worst case all to all user traffic. Theoretically, good performance can be obtained when two clusters are connected with a few links. In the Anglova scenario, the traffic rate could be increased from 3.6kbps using a classical round robin to 10kbps using an optimal schedule tuned to the demand.

G. Source Admission Control

Simply, avoiding to send data to temporarily disconnected node could reduce congestion and improve the perceived QoS. So, resource allocation was investigated with Source Admission Control (SAC) to offer a more reliable communication system in presence of congested nodes and network disconnections.

An omniscient SAC was implemented to detect network disconnections in a dynamic environment. Omniscient SAC drops the packet at the source node when routes are not available. Current SAC only support one type of traffic, but a new version is being developed to support any application traffic. A store and forward mechanism leveraging the global graph will be considered to predict network disconnection or local congestion. The packet can be stored and forwarded later or the traffic rate will be reduced when the schedule cannot keep up with the demand.

H. Future work using GNN

Our best routing scheme (ODR) should be modified to account for the traffic demand. Furthermore a distributed version of ODR is required. Distributing the link states used by ODR appears rather simple knowing that OLSR is doing just that, but many practical details remain to investigated. A current investigation seeks to train a GNN to predict the global graph of the network from local information such as the DAT metric ij or the link quality between nodes. A temporal graph prediction remains a challenge for wireless communication as the link quality can greatly vary in time. Predicting realistic traffic scenario is also a future challenge which could benefit from a GNN approach. Merging AI based solutions for V2V and V2I will be key to offer acceptable QoS for V2x use cases.

V. Conclusions

As was stated, the importance of wireless communications in ITS systems is permanently increasing, and it is evident that efficient and reliable data delivery is often becoming one of the critical factors to guarantee proper service provisioning. In this paper, we have discussed the role of advanced AI/ML tools in future vehicular wireless communications networks. Based on the three selected examples - i.e., distributed learning, proactive QoS provisioning, and application of GNNs, we have shown the great potential of such solutions in improving the performance of vehicular communication networks. We claim that distributed approaches may provide numerous benefits here, as network nodes may, on the one hand, exchange information between themselves, enriching their individual level of knowledge; on the other - they may distribute the computation and processing load among multiple elements. In that context, the application of advanced and new solutions, such as GNNs, creates new areas for performance improvement. Moreover, the integration of predictive QoS schemes based on AI has the potential to ensure seamless service provisioning despite the highly variable conditions faced in vehicular environments.

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