Predictive Quality of Service (PQoS): The Next Frontier for Fully Autonomous Systems

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Abstract—Recent advances in software, hardware, computing and control have fueled significant progress in the field of autonomous systems. Notably, autonomous machines should continuously estimate how the scenario in which they move and operate will evolve within a predefined time frame, and foresee whether or not the network will be able to fulfill the agreed Quality of Service (QoS). If not, appropriate countermeasures should be taken to satisfy the application requirements. Along these lines, in this paper we present possible methods to enable predictive QoS (PQoS) in autonomous systems, and discuss which use cases will particularly benefit from network prediction. Then, we shed light on the challenges in the field that are still open for future research. As a case study, we demonstrate whether machine learning can facilitate PQoS in a teleoperated-driving-like use case, as a function of different measurement signals.

Index Terms—Predictive Quality of Service (PQoS), autonomous systems, autonomous driving, IoT, machine learning.

I. INTRODUCTION

5G (and beyond) innovations are pushing toward the transition from automated to autonomous systems to safely operate without human intervention [1]. For example, driverless cars will be able to mitigate accidents caused by human error, improve the traffic flow, and reduce emissions. On the same wave, collaborative machines in the Industrial Internet of Things (IIoT) domain [2] are making their way into the market to support search and rescue (e.g., military drones), telemedicine (e.g., surgical robots) and workflow optimization (e.g., industrial actuators), as well as to enhance agriculture and logistics (e.g., connected tractors), facilitate diagnostics (e.g., smart home/city sensors), and improve security (e.g., software-defined networks).

Besides novel communication technologies and network architectures, the deployment of autonomous systems is accelerated by recent developments in the areas of artificial intelligence (AI) and machine learning (ML), that will make it possible for autonomous devices to gather huge volumes of data and self-optimize [3]. However, the dynamic nature of the environment in which the autonomous machines run and operate may significantly complicate network management, which may be unable to fulfill a very demanding set of Quality of Service (QoS) requirements (e.g., in terms of very low latency, ubiquitous/robust coverage, and huge downlink/uplink data rate) [4]. In particular, unanticipated QoS degradation may restrict the adoption of safety-critical autonomous applications characterized by extremely high reliability constraints, due to the potentially catastrophic impact of a communication failure.

In this context, several groups are promoting Predictive Quality of Service (PQoS), defined as a mechanism to provide autonomous systems with advance notifications about upcoming QoS changes [5]. Compared to 5G-like reactive strategies, which respond to unanticipated events only after they occur, a proactive behavior gives applications more time to react and permits more efficient network adaptations. For example, if the upcoming QoS is not sufficient to handle teleoperated driving, the network may preemptively schedule human takeover to prevent unsafe situations. Similarly, the resolution of data shared for applications like unsupervised factory control should be dynamically adapted to accommodate bitrate variations, while communication resources should be allocated as a function of the foreseen network capacity. The time scale of the prediction depends on the use case of interest, as well as the current network dynamics. In general, while for 5G and its predecessors the QoS predictions are typically provided on a slot/frame granularity, future autonomous systems shall support PQoS over a larger time horizon, which may span several minutes or even hours [3]. This implies that current prediction mechanisms, based on Bayesian filtering or linear regression [6], should be adapted to permit full-network planning, e.g., leveraging learning-based methods to improve target state estimation [7].

While PQoS is generally referred to real-time multimedia/web applications [11], in this paper we characterize PQoS for future autonomous systems. First, we describe several use cases (and their requirements) for which PQoS is desirable, with a focus on connected autonomous driving and IoT applications (Sec. [II]). Then, we present possible directions to make autonomous systems predictive over a large horizon (Sec. [III]). We provide a full-stack perspective with considerations related to both core and radio access network aspects, thus stimulating further research on this topic. As a case study, we validate the feasibility of predicting QoS (in terms of uplink throughput) of vehicular applications via machine learning (Sec. [IV]). Our results show that deep neural networks (DNNs) can result in more accurate long-term estimates (80% reduction in average error) compared to a simple linear regression model. Moreover, we provide numerical evidence of which data should be acquired and processed to facilitate network prediction. We demonstrate that the Signal to Interference plus Noise Ratio (SINR) is the most important feature input for PQoS, achieving a prediction error as low as 4% of the maximum throughput.
range.

II. PQoS: USE CASES AND SERVICES

Originally, system prediction was developed with functional safety in mind, to preemptively evaluate the potential safety risks caused by the malfunctioning behavior of electronic/electric systems in vehicles. Today, autonomous driving systems also implement inter/intra-machine communication, which requires network predictions too, as approved for 5G networks by the 3rd Generation Partnership Project (3GPP) [12]. While functional safety expects the system to be shut down in case of system fault, PQoS should support mechanisms to gracefully change the operational mode to ensure that autonomous vertical applications satisfy strict latency/reliability constraints. In this context, this section reviews some use cases, as illustrated in Fig. 1, for which PQoS is desirable. Specifically, we focus on (i) the objective of the prediction, (ii) the QoS Key Performance Indicators (KPIs) to be fulfilled, (iii) the PQoS window, i.e., the time period for which PQoS analytics is requested, and (iv) the appropriate reactions to be triggered before the predicted QoS change occurs.

A. PQoS for IIoT Applications

Predicting QoS should allow industrial applications to continue operation with adapted functionality under the upcoming QoS conditions. In the following, we analyze two industrial automation use cases, selected based on current research trends and the interest in industry.

a) Closed-loop control: Closed-loop control is crucial in industrial processes to guarantee safe interaction between a production machinery and its human operator(s) (e.g., in an assembly line). Based on environmental sensors, which continuously measure physical parameters (e.g., temperature, pressure) from the production process, the autonomous system configures, monitors, and maintains machines even if the communication service is temporarily unavailable, so as to avoid/minimize accidents and damage of property. Due to the critical nature of these applications, determinism becomes a crucial requirement: a 99.99999% reliability is required, while the maximum latency is typically set to around 150 ms, since sensor’s measurements are not expected to change rapidly [8].

Role of predictions. Network predictions are useful to prevent harm to human operators in case of malfunctions. Specifically, we focus on (i) the objective of the prediction, (ii) the QoS Key Performance Indicators (KPIs) to be fulfilled, (iii) the PQoS window, i.e., the time period for which PQoS analytics is requested, and (iv) the appropriate reactions to be triggered before the predicted QoS change occurs.

| KPI | IIoT Applications | V2X Applications |
|-----|------------------|-----------------|
|     | Closed-loop control | Mobile robot control | HD map collecting and sharing | Teleoperated driving | High-density platooning |
| Services | guarantee safe interaction between production machinery and human operators | interconnect several robots over a large area to fulfill a common task | build an HD map of the environment to improve safety and provide optimal route selection | control of vehicles by a remote operator (either human or software) | enable vehicles to travel in close proximity at high speeds to decrease fuel consumption |
| Latency [ms] | 150 | From 1 to 500 | ≤ 100 | ≤ 50 | from 10 to 25 |
| Reliability [%] | from 99.9999 to 99.99999 | > 99.9999 | 99 | 99 (uplink) 99.999 (downlink) | from 90 to 99.999 |
| Data rate | very low | 30/50 Mbps | up to 500 Mbps for HD sensor data | 30/50 Mbps | 30/50 Mbps |
| Role of predictions | prevent harm to human operators in case of malfunctions | improve productivity | ensure reliable services | guarantee a minimum safety level at all times | ensure continuous operation (even without connectivity) |
| Prediction window | milliseconds | seconds/minutes | minutes/hours | seconds/minutes | seconds/minutes |

Fig. 1: Use cases in the industrial (IIoT) and vehicular (V2X) domains in which PQoS can be desirable, and relative KPIs according to [4], [8]–[10]. The last row indicates the prediction window, i.e., the time horizon over which QoS should be predicted and network countermeasures should be taken.
b) Mobile robot control: An automated production facility may need to interconnect several robots over a large area to fulfill a common task (e.g., high-precision cooperative carrying). To do so, mobile robots stream data from their on-board sensors (e.g., cameras and laser scanners) to a remote guidance control system, which then processes the received information and manages the traffic. Sensor data transmission poses severe constraints in terms of throughput (above 10 Mbps) which may be difficult to handle with standard communication technologies. Additionally, cooperative machines have to be synchronized in time: the latency requirement ranges from 500 to 1 ms, depending on the degree of automation.

Role of predictions. Network predictions promote improved productivity. Based on them, the system can indeed self-reconfigure (e.g., changing the operation speed and/or route) and/or transition to safe mode in a graceful manner, thus supporting continuous operation even when the communication system is temporarily unavailable. Robots may also adapt their sensors’ properties (e.g., the resolution for remote control) to alleviate the burden on the channel during data transmission. The prediction window is generally consistent with the time frame at which the environment changes, i.e., a few seconds/minutes.

B. PQoS for Vehicle-to-Everything (V2X) Applications

Autonomous driving systems have strict QoS requirements that need to be satisfied, despite the highly dynamic nature of the V2X environment. In the following, we review three use cases where PQoS can ensure efficient and reliable driving.

a) High-definition map collecting and sharing: Autonomous vehicles are equipped with several sensors that gather information from the surrounding environment. More accurate scene understanding can be guaranteed if vehicles broadcast sensors’ observations to remote/edge servers. These nodes collect, process, and combine the received data to build a regional high definition (HD) map of the environment to improve safety and provide optimal route selection to the vehicles. Data sharing, while involving relatively loose latency (≤ 100 ms) and reliability (99%) requirements, may imply multi-gigabits-per-second transmission rates for raw perception data.

Role of predictions. Based on network predictions, the remote server can (i) regulate the number of vehicles required to disseminate HD map updates, so as to reduce network congestion, and (ii) adapt the periodicity of generated messages, to ensure reliable services. The central controller can also adjust the map collection and sharing parameters, such as the level of compression/resolution for sensors’ data. A more efficient approach is to select and share only the most valuable environmental elements in the scene (e.g., pedestrians and cyclists), even though this requires the data to be pre-processed before transmission, which may be hard to complete on board of vehicles. Short-term predictions are desirable, to capture the dynamics of the environment (a prerequisite in safety-critical situations).

b) Teleoperated driving: Teleoperated driving enables the control of vehicles by a remote operator (either human or software). The control center must receive/process perception data, including videos from on-board camera sensors, whose data rates can be in the order of hundreds of Mbps for high-resolution transmissions. At the same time, driving decisions from the remote driver must be delivered to the host vehicles with low latency (in the order of 50 ms or less), since higher delays may result in reduced driving responsiveness. Moreover, a 99% (99.999%) reliability should be supported in uplink (downlink) to receive driving commands, in addition to other parallel (sensor-based) safety countermeasures to promote more accurate driving operations.

Role of predictions. Based on network predictions and in case of QoS degradation, the system should gracefully transition to safe mode, thus guaranteeing a minimum safety level at all times. For example, if a certain route is congested, PQoS may assist the control center in adapting the vehicle’s speed and trajectory. Even though the system should predict the entire end-to-end trip in advance and organize the driving experience accordingly, full-path planning is complicated in dynamic environments, thus making medium-term prediction (e.g., within a time frame of a few minutes) in critical areas (e.g., close to crossroads or intersections) more appropriate.

c) High-density platooning: Platooning enables vehicles to cooperatively travel in close proximity at high speeds, to decrease fuel consumption and traffic congestion. Platooning can be supported by a cloud assistant application, which gathers status information from the platoon head/leader, such as common mobility patterns (e.g., speed, heading, intended maneuvers) and perception data from on-board sensors, and decides the behavior and configuration of the platoon. QoS requirements are given according to the desired degree of automation: while the required latency for collecting and processing status updates and broadcasting platooning decisions ranges from 10 to 25 ms depending on the distance, the required reliability ranges from 90% to 99.999%.

Role of predictions. Network predictions are useful to estimate when platoon members are out-of-coverage, and ensure continuous operation even without connectivity. Based on them, the cloud assistant can manage the platoon formation, e.g., regulating join/leave operations, the number of platoon members, the distance between vehicles and their speed. It can also control local perception parameters, such as reducing the number of vehicles required to share sensors’ data to mitigate the traffic load on the channel. In case QoS degradation or outage (e.g., in tunnels) is foreseen, the cloud assistant may instruct the platoon leader to support driving activities by coordinating resources autonomously over the sidelink, or request human intervention. A medium/long prediction window of a few seconds/minutes is beneficial to efficiently capture the road dynamics.

III. ENABLING PQoS: TECHNOLOGIES AND TRENDS

Besides introducing PQoS procedures in Sec. III-A we distinguish between Core Network (CN) and Radio Access Network (RAN) aspects in Sec. III-B and III-C, i.e., the two main 4G/5G system architecture components.
A. Algorithms and Procedures

According to the 5G-ACIA, dependability in autonomous systems is crucial to provide information about the network changes ahead of time. In this context, PQoS enables the autonomous system to take actions before machines go into a down/failure state. In this condition, either the data units do not arrive correctly within a given latency constraint (i.e., network service failure), or the application cannot continue to function, given its settings and the network status (i.e., application service failure). We define the survival time as the time that the application service can “survive” without the network service. As an example, in the top part of Fig. 2 (where each “0” or “1” represents a failure or success for one transfer interval, respectively) the application service has a survival time of two transfer intervals and does not leverage advance notifications of network service. In this scenario, the application service can “survive” two consecutive failures (depicted as “case 1” in the figure), but cannot survive three (depicted as “case 2”). In the bottom part of Fig. 2 we now assume that PQoS provides advance notifications several transfer intervals ahead of time. This would allow the application service to adapt to “case 2” by regulating its survival time to three transfer intervals, thereby ensuring that there is no disruption, at the expense of reduced QoS performance.

From the example above, it appears clear that it is vital to correctly estimate the time evolution of the network and react accordingly. The optimal strategy depends on the time horizon of the prediction, as well as on its “quality” (e.g., in the form of probabilistic confidence interval of the predicted value). While for short-term prediction (e.g., in the context of functional safety) faults occur mainly due to hardware imperfections, in case of longer-term predictions targeted by PQoS ML, radio and network conditions are the main culprit for faults: PQoS aims at providing methods able to predict the network behavior with high accuracy. Compared to traditional prediction algorithms like linear regression and filter-based models, which do not efficiently handle large amounts of input data or are unable to provide predictions for non-linear relationships between features and labels, ML solutions hold the promise of more accurate predictions [13]. Notably, DNNs are able to learn meaningful relationships based on network observations (including radio and network conditions, available resources, predicted mobility patterns, etc.), and return the possible actions to sustain QoS in case of unseen conditions without pre-programmed/a-priori rules. Furthermore, methods such as transfer learning (TL) can be leveraged to transfer the knowledge acquired from one scenario to another (e.g., in which communicating nodes are deployed in different locations), without the need to learn from scratch.

However, applying ML-based approaches introduces several trade-offs. On one side, model training requires significant computational power and time, together with the availability of a large amount of data to build robust predictors. Additionally, model retraining, due to data distributions drifting over time in dynamic environments, involves additional overhead, which may not be tolerated by safety-critical use cases. Nevertheless, the above issues can be mitigated by adopting offline (rather than online) training, or by delegating the training operation to external processors: once the model is trained, inference can be done even on devices with limited computational requirements.

B. PQoS Core Network (CN) Aspects

In terms of the CN (responsible for end-to-end connection management and Internet access), the initial work on PQoS has been done by vertical industry associations. Specifically, following the initial pre-standarization efforts by 5GAA [5] and 5G-ACIA [8], the 3GPP defined the so-called network data analytics function (NWDAF) to provide analytics services to 5G CN functions [14]. NWDAF is a key enabler for network automation, aggregating data, and providing analytics using either a request or a subscription model. NWDAF enables several functionalities [15] that are PQoS-related. They can be grouped as follows:

- **QoS provisioning and adjustment**, designed to support the requirements that different QoS parameters and traffic types mandate from the network, along with their timely adaptation and related data traffic handling;
- **mobility/topology-related** management, to assist edge computing functions, and identify the area(s) of network topology that might have oscillating QoS;
- **policy adjustment**, designed to support sharing of analytics, determine the appropriate policy based on them, and ultimately ensure predictable network performance.

While not yet fully developed in 3GPP specifications, the above functionalities are a good starting point to enable PQoS. Whether NWDAF should be implemented in software or hardware is still unclear. Although the former approach permits to host NWDAF facilities at low cost and closer to the end machines, thus promoting lower latency, the latter has access to more computational resources, at the expense of flexibility.

C. PQoS RAN Aspects

Having PQoS enabled in the CN only will not suffice for safety-critical and time-critical applications that are frequent in IIoT and V2X. To reduce the latency and increase the
flexibility, following the architectural aspects and CN functions defined in the scope of NWDAF, standardization activities have started in RAN Working Group 3, where a study item has recently been approved to define the high level principles for RAN intelligence (mainly responsible for radio-resource handling and data transmission) enabled by AI [16]. While still in its infancy, the study promises to support PQoS functionalities.

In terms of technical enablers in RAN-side prediction, we highlight the following promising approaches.

- **Radio map prediction.** Predicting the physical aspects of radio propagation (e.g., path loss or SINR, that is generating “radio maps”) shows promising results [17]. Specifically, using measurements or ray tracing as “ground truth” for radio maps and applying ML-based approaches to predict the maps in foreseen locations can serve as an underlying “layer” for throughput, latency, and other application-level QoS parameters.

- **Predictive adaptation of radio parameters.** The RAN should convert QoS estimates into appropriate network decisions if service requirements are not satisfied. Besides operating directly on the mobility patterns, the RAN may undertake lower-layer actions, e.g., changing communication mode, adapting the radio resource allocation based on the available network capacity, or modifying the system numerology and/or the communication spectrum.

- **Predictive scheduling.** The RAN should make scheduling decisions in advance of the network changes. Depending on whether or not network coverage will be guaranteed in future time instants and geographical locations, resources can be scheduled either by the base station or autonomously by the machines, respectively.

In terms of RAN-based prediction, while lower-layer metrics, such as the users’ locations or the SINR, may be able to capture both signal strength and propagation conditions, higher-layer parameters (e.g., average data rate, end-to-end latency, or packet delivery ratio) may be used to train more accurate prediction models. In Sec. IV we evaluate which data can best support QoS predictions for a specific scenario.

IV. PQoS PERFORMANCE EVALUATION: A CASE STUDY

In Sec. III we reviewed how machine learning could facilitate network prediction. As a case study, we now evaluate the ability of machine learning to predict the QoS of V2X applications using measurement data. We describe our measurement scenario in Sec. IV-A and present the numerical results in Sec. IV-B.

A. Measurement Scenario and Parameters

Our measurement campaign was performed in Munich, Germany. The scenario (illustrated in Fig. 3) was defined so as to resemble the teleoperated driving use case (Sec. II-B), in which vehicles transmit video stream(s) to the teleoperating center with a maximum uplink throughput of 40 Mbps [10].

The measurements were collected at 3.41 GHz, with 40 MHz of bandwidth and antenna gain of 15.5 dBi (5 dBi) at the base station’s (user’s) side. We collected the following information, referred to as “input features” in the remainder of this paper: uplink/downlink throughput, SINR (measured as the ratio of the signal power to undesired interference plus noise power) and Reference Signal Received Power (RSRP) (an indication of the channel quality at the carrier level) for each base station antenna sector, location (longitude, latitude, altitude) and velocity of the vehicle. The measurements were collected on a relatively small loop with stable traffic/interference conditions. This makes our input features able to predict the system for any time horizon. In a more dynamic environment, the applicable time horizon will depend on the rate of variability of these parameters.

The collected dataset was used to predict the throughput using several machine learning approaches. In particular, we employed linear regression and DNNs, and used different input features to evaluate which of them (or their combination) resulted in the best prediction of the uplink throughput. The motivation for using these two methods is to evaluate whether general-purpose prediction methods – one more computationally simple (linear regression) and the other more complex but potentially broadly applicable (DNN) – can be effective at predicting the uplink throughput.

The DNN we used for prediction consists of a normalization layer, followed by three dense layers. The first two dense layers have 64 outputs and use “ReLu” activation, with the final dense layer resulting in one output (i.e., the predicted throughput value). The collected measurement dataset, containing approximately 3100 samples, was divided into training and testing datasets. The training dataset contained 90% of the randomly selected samples, with the remaining 10% used for testing.

B. Simulation Results

We first explored the relative benefit of each of the input features. SINR and location emerged as the dominant features in case of both linear regression and DNN. This is expected since (i) the SINR is proportional to the throughput (with SINR above 10 dB nearly always resulting in the maximum achievable throughput of 40 Mbps), and (ii) both training and
TABLE I: Mean absolute and relative error on testing data for different prediction methods.

| Prediction algorithm                         | MAE (Mbps) | Avg. throughput error (%) |
|----------------------------------------------|------------|---------------------------|
| Linear regression, location only             | 2.21       | 6.5 %                     |
| Linear regression, SINR only                 | 2.19       | 6.4 %                     |
| Linear regression, SINR and location         | 2.08       | 6.1 %                     |
| DNN, location only                           | 0.92       | 2.7 %                     |
| DNN, SINR only                               | 0.46       | 1.4 %                     |
| DNN, SINR and location                       | 0.40       | 1.2 %                     |

Fig. 4: Training error (in terms of MAE) for different prediction approaches of the uplink throughput, as a function of training epoch, i.e., the number of cycles through the full training dataset.

Testing datasets were collected along the same route, and thus incorporate the same location information. Furthermore, the remaining input features have been observed to be insignificant or even detrimental in the presence of SINR and distance features, due to reduced learning rate. Specifically, the speed of the user was not high enough to exhibit measurable variations due to Doppler, whereas the RSRP per sector was better accounted for as part of the SINR. Moreover, despite the separation in frequency, the downlink SINR and throughput have shown high correlation with their respective uplink counterparts, indicating that the dominating factor on the channel was large scale fading.

Based on these early results, we explored six prediction models with the following combinations of input features:

- Linear regression (or DNN) with location only;
- Linear regression (or DNN) with SINR only;
- Linear regression (or DNN) with both SINR and location.

Fig. 4 shows the training error, measured in terms of mean absolute error (MAE), of the uplink throughput over the duration of training for the six models. All linear models converge very quickly to their best performance (within 20 epochs), irrespective of which features are used. Notably, the combination of SINR and location results in a markedly better performance at virtually no expense of further training. However, all linear regression models converge to a minimum of about 2 Mbps MAE (as reported in Table I). This indicates that the linear model is overly simple in describing the relationship of the input features and the predicted uplink throughput, thus calling for more advanced approaches, as discussed in Sec. III-A. Specifically, linear regression optimizes predictions only for throughput samples above 35 Mbps, which make up almost 90% of the data we collected.

On the other hand, while all three DNN models require increased training (over 50 epochs), they converge to below 1 Mbps MAE. In particular, the “DNN, location only” model results in MAE of 0.92 Mbps, while the “DNN, SINR only” model further reduces the MAE to 0.46 Mbps (see Table I) with a considerably faster rate of convergence. This indicates a more direct relationship between SINR and throughput. Finally, the “DNN, SINR and location” model ultimately results in the lowest MAE of 0.4 Mbps, even though this requires 150 epochs of training compared to around 50 for the “DNN, SINR only” model. While this does not affect the real-time prediction performance, since the training phase is performed offline, convergence time should still be minimized as much as possible to facilitate computationally efficient predictions and promote faster retraining.

Similar conclusions can be drawn from Fig. 5 which shows the comparison of the measured values of throughput in the testing dataset and the prediction by different algorithms. Due to the smaller number of samples in the lower range of throughput, all linear regression approaches result in high error. On the other hand, DNN approaches result in both lower and more uniform error across the range of throughput values. For completeness, Table II also shows the average throughput error, calculated as the ratio between the MAE and the mean uplink throughput of the collected dataset (34 Mbps).

Our results indicate that SINR is the single most important feature, among those collected, when it comes to predicting throughput. Notably, SINR can better generalize to unseen locations, as it incorporates in a single value both the properties of a certain location and the transmitter/receiver distance. Moreover, SINR subsumes any temporal effects of the channel, which helps with long-term predictions, a fundamental prereq-
uisite for PQoS applications. We further explored the impact of reducing the precision of the collected SINR (i.e., the accuracy of radio maps) by introducing noise. Specifically, increasing an SINR root mean square error (RMSE) from 0 to 4 still resulted in a MAE of less than 1 Mbps, whereas an SINR RMSE of 10 resulted in 1.5 Mbps MAE. This is a positive result, since it indicates that radio maps do not need to be perfect to still obtain a reasonably good throughput prediction (i.e., within 4% of the maximum throughput range).

V. CONCLUSIONS AND NEXT STEPS

Based on the current research and industry alliance efforts, we analyzed the ability of PQoS to accurately predict the network performance of autonomous systems, as a means to gracefully change their operational mode if the target performance cannot be achieved. We discussed the techniques – most notably those relying on machine learning – that help enable PQoS in the core and radio access parts of the network. Notably, we draw the community’s attention to the development of mechanisms to adjust end users’ mobility/topology patterns, scheduling decisions, and radio parameters, to satisfy service requirements in view of the predicted QoS. We exemplify the potential benefits of PQoS through a real-world example of predicting uplink throughput in V2X via ML techniques. Our simulations prove that DNNs based on SINR measurements can result in accurate predictions, while involving longer training than a linear regression approach.

As identified in Sec. III, there is a lot of work remaining for PQoS to fulfill its promise. In particular, techniques that allow RAN-based predictions need to be enabled, in particular those that can provide benefits using relatively small and local input information. Furthermore, a tighter integration between RAN and core network is required, with prediction information flowing both ways for some use cases (e.g., teleoperated driving). Finally, little work has been done on incorporating the sidelink into the PQoS ecosystem. Combined with distributed PQoS algorithms, sidelink holds the promise of low latency, local prediction with minimum uplink/downlink control from the network.

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