Digital Twins for Maintaining QoS in Programmable Vehicular Networks

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Abstract*—Digital twins are virtual replicas of the real world that capture precise interactions between actual devices and the environment in which they operate. Enabled by advancements in computing and ubiquitous software, digital twins may receive data from the real world as well as generate virtual datasets for making decisions that ultimately influence the complex real-world actions. As a use case, we propose applying digital twins in connected and autonomous vehicles for exceeding the wireless quality of service (QoS) in non-line-of-sight (NLOS) scenarios. Key to this vision is incorporating programmable base stations (BS) and reconfigurable intelligent surfaces (RIS) that mitigate the frequent blockages in dynamic vehicular networks. In our method, a LiDAR sensor mounted autonomous car detects obstacles between itself and the base station (BS) it is connected to during its voyage in order to predict NLOS situations, which are then reported to the BS, where the digital twin is deployed. Upon an obstacle notice, the digital twin is triggered and runs ray-tracing by placing an obstacle in the digital twin's virtual map in order to determine i) BS settings, such as transmit power, antenna directivity, wireless standard, and ii) RIS configurations that will maintain the QoS along the autonomous vehicle's trajectory. We validate the feasibility of our proposed method using real life LiDAR data and Wireless InSite ray-tracing software, in which we determine the base-station and RIS configurations to maintain QoS by testing wireless standards, i.e. 802.11ac and LTE, antenna patterns and directivity, and transmit power levels. Results reveal that can detect obstacles from $11\,\mathrm{m}$ away, giving enough time for BS to reconfigure itself and RIS within city speed limits, and reduce the required transmit power by $2.32\times$, on average in dBm, compared to the LOS scenarios through RIS.

***Index Terms*—digital twin, autonomous cars, intelligent surfaces, quality of service**

I. Introduction

A *digital twin* is a replica of a physical system in a virtual environment, which captures the properties of its real-world counterpart as well as interactions among the replicated components [1]. By having a continuous information exchange cycle between the virtual and real worlds, a digital twin enables tracking state-changes of the real entity and studying the impact of any configuration setting. This way, not only a real system can be tested before its deployment, but also after the deployment the system can take early actions through machine learning and artificial intelligence (ML/AI) models deployed in the virtual world [2]. Despite such a groundbreaking potential, previous digital twin implementations in manufacturing, oil and gas, construction, and bio-engineering fields rely on one-time modeling, which is also the case in the wireless examples, where digital twins are used only to determine base station locations [2]. In this paper, we propose a programmable and interactive digital twin for dynamic vehicular networks, with the goal of maintaining quality of service (QoS), using reconfigurable intelligent surfaces (RIS) and reconfigurable base stations (BS), which can be Open Radio Access Network (O-RAN) compliant [3].

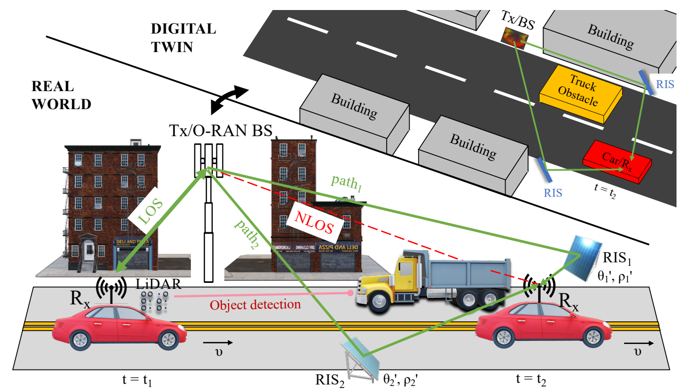

Fig. 1: The proposed framework, in which we utilize programmable base station and RIS for maintaining QoS during NLOS cases in vehicular networks with the help of digital twins.

•**Scenario of Interest:** As shown in Fig. 1, our scenario involves a moving vehicle (*subject vehicle*) with the speed of ν, where the Doppler effect is negligible, carrying a receiver (Rx), communicating with a BS that has the transmitter (Tx) with LOS at time t_1. However, at time t_2, as the vehicle moves, a large obstacle, e.g. another vehicle, blocks the direct communication between Tx-Rx. This creates an NLOS case, which in turn drops the QoS at the moving vehicle. Mitigating the impact of NLOS communication necessitates addressing many unknowns, such as detecting the NLOS situation, its duration, and identifying the transmission power (P_{Tx}) and antenna direction that ensures connectivity.

•**Motivation for Digital Twins:** In real life, making dynamic network decisions is complicated and consumes a lot of precious wireless resources without guaranteeing the timing requirements of fast-pacing vehicular networks. There are several methods to mitigate the performance degradation in NLOS communication scenarios, such as multiple input multiple output (MIMO) beamforming. However, long training time [4] for initiating the communication link makes it impractical for highly dynamic environments. ML/AI based algorithms are another potential candidate for solving this performance degradation, but it is limited by the environments seen during training time. In case of data distribution shifts, ordinary ML/AI algorithms fail in prediction accuracy [4]. Therefore, we propose utilizing digital twins in order to address the aforementioned problems, given that digital twin is a replica of the real world, having a complete view of the network dynamics with the ability of modifying settings on the fly.

•**Motivation for Programmable Vehicular Networks:** Determining correct strategies to address the drop in QoS in NLOS cases is essential. One way to achieve this is to predict a vehicle's trajectory and update various network resources at the Tx accordingly, by benefiting from digital twin's flexibility and complete view of the network. These updates could include increasing P_{Tx}, switching to another wireless standard, e.g. cellular or WiFi, changing the antenna pattern in use, or directing one or multiple beams to certain directions. Deciding optimal parameters among many possibilities requires high computation power, which can be addressed by newly introduced intelligent components of Open Radio Access Networks (O-RAN) [3], which is a next generation cellular system requiring ML/AI models to yield outputs with time restrictions, e.g., $< 1s$.

The aforementioned opportunities by digital twins open further doors for enhancing the QoS at Rx during NLOS scenarios. Accordingly, we propose using RIS, as shown in Fig. 1, that are able to alter the phase (θ) and direction (ρ) of the reflecting electromagnetic waves with the goal of constructively adding the signals at a target receiver. We envision connecting RIS to BS/Tx, which programs RIS properties for constructive signal addition upon predicting NLOS cases.

•**Proposed Approach:** In this paper, we propose the use of digital twins in vehicular networks in order to maintain QoS in NLOS scenarios at the same level as LOS through intelligent surfaces that will work in coordination with the BS. First, we create a virtual replica of the experiment setup that is composed of a map, buildings, realistic wireless settings, obstacles, RIS, and vehicle movement representation, which collectively make up the digital twin and is deployed at BS. The subject vehicle uses its on-board LiDAR sensor in combination with local deep learning to detect obstacles between Tx-Rx, i.e. NLOS cases, which triggers the digital twin. Detecting obstacles at a distance in advance gives BS enough time to run the digital twin, determine optimal wireless settings, and reconfigure its resources to mitigate the NLOS effect. Upon triggering, the digital twin places the obstacle in the virtual world, using the coordinate and dimension information that was uploaded to BS by the subject car, and runs a ray-tracer to determine the drop in received power at the Rx (subject vehicle), compared to the LOS scenario. Then, the BS determines the optimal wireless settings using two strategies: i) modifying BS sources, such as P_{Tx}, beam directivity, and communication standard in a way that P_{Rx} is maximized and ii) modifying phase (θ) and direction (ρ) of the reflecting signals from the RIS using passive antennas such that the reflected signals are added constructively at the Rx. Method ii) has also the flexibility to modify BS sources.

In this framework, main the challenges are a) creating a virtual world that is accurate enough to represent the real world without exorbitant details, b) correctly detecting obstacle location and its size, c) strategically placing and configuring RIS while updating wireless resources at the BS.

•**Summary of Contributions:**

- We create a digital twin that is a virtual and accurate representation of the real-world experiment setup, which captures the interactions among moving entities.
- We propose a framework that includes strategies to maintain QoS during the NLOS scenarios by updating wireless resources at the BS and modifying RIS configuration.
- We detect vehicles that block LOS communication between Tx-Rx, by minimally modifying the PointPillars algorithm [5] using the LiDAR component of the real world FLASH dataset [6].
- We demonstrate the feasibility of our idea in a ray-tracing tool, Wireless InSite [7], by comparing LOS cases with the strategies we identify above. We form baseline in LOS scenarios and then implement our two solutions to show the improvement and practicality of our proposed strategies.

In the remainder of the paper, we first review related work on digital twins, its applications in vehicular networks and RIS. Then, we detail our vision supported by a rigorous simulation and experiment design, and provide performance evaluation. We conclude with future directions and challenges.

II. Related Work

A. Digital Twin

Though the idea of digital twins blossomed in 1960s for NASA's Apollo space program [1], the first real world applications of digital twin emerged in the aviation and then manufacturing industry [12]. Recently tech giants, such as Microsoft, Siemens, General Electric started to invest in digital twins, too [1].

Given the increasing complexity and demand in wireless systems, digital twins have found their way into internet of things (IoT) as well [12]. Next generation wireless systems have three main aims i) high data rate, ii) large scale seamless service, and iii) low latency. However, realizing these goals simultaneously is not feasible using traditional and physical device dependent methods, because the calculation burden and usage of wireless sources inhibit service quality. Fundamentally, digital twins for wireless networks are used for resource allocation [10], spectral efficiency [12], energy efficiency [11], customization [8], and security measures [9]. Depending on the computation and latency requirements, virtual world/digital twin can be deployed at edge, cloud, or edge-cloud based infrastructures [2]. Applications of such a scheme include the use of metasurfaces to increase network capacity, mitigating unreliability by deploying digital twins at the edge, and mobile cell tower management [12].

B. Digital Twins for Vehicular Networks

Liao *et al.* [8] assert that large scale traffic data inhibits the purpose of digital twins by exhausting computation sources. Thus, the authors propose an on-demand digital service model, where vehicles are able leverage digital twins by applying blockchain principles for intelligent transportation. El Marai *et al.* [9] propose deploying digital twin boxes for capturing

Paper	Objectives	DT-RW Interaction	Wireless Standard	Implementation	Data Traffic	Vehicle Traffic	Method	Outcomes
[8]	Different level of need in DT in dynamic environments	On-demand, Edge/Cloud	Not specified	Simulation	Massive edge data	Urban traffic	Blockchain, Double auction	Intelligent transportation
[9]	Obstacle detection for DT assisted autonomous driving	Unspecified periodicity, Edge/Cloud	Not specified	Simulation	Video, GPS, weather	Urban traffic	Single-Shot Detector (SSD)	Self-driving cars, Smart mobility
[10]	Cooperative ramp merging for connected vehicles	Continuous, Cloud	4G/LTE	Real cars, Phone app	Raw position, vehicle speed	Vehicles in ramp merging	Nonlinear Autoregressive Neural Networks	Safety, less traffic, low comm. delay
[11]	Resource and scheduling allocation for vehicles	Continuous, Edge/Cloud	Not specified	Simulation	Network topology, computing load	Random	Stackelberg game	Vehicle satisfaction and energy efficiency
Ours	Maintain service in NLOS	Continuous, Edge/Cloud	O-RAN, LTE, and WiFi	Wireless InSite	LiDAR	Urban traffic	Deep Learning, RIS	Improved QoS

TABLE I: Overview of state-of-the-art methods solving different issues in the vehicular networks using digital twins. We highlight our contribution in the last row, which differs by the usage of programmable RIS in the vehicular contexts in digital twins.

video images and GPS coordinates of the dynamic vehicular environment to process with the goal of detecting vehicles and pedestrians, which are then sent to digital twins for decision making in autonomous driving. Liao *et al.* [10] aim to ease traffic jams at ramp merges through vehicle-to-cloud based digital twin, which they implement using real cars and an app on each vehicle, transmitting vehicle's raw position and speed to the cloud over 4G/LTE infrastructure. At the cloud, where the digital twin in deployed, a nonlinear autoregressive neural network based model uses the transmitted data to optimize the vehicle's movements. Sun *et al.* propose a digital twin framework for computation offload, which consists of ground vehicles, road side units (RSU), and unmanned aerial vehicles (UAV) [11]. By utilizing a two stage Stackelberg game, the authors assign ground vehicles to RSUs for offloading. They show the feasibility and convergence of their proposed mechanism in simulation. The selected relevant works are summarized in Tab. I.

C. Reconfigurable Intelligent Surfaces

The concept of RIS refers to an array of programmable electromagnetic structures that are used to control the reflective properties of the surface in order to direct signals to a particular target for maximizing the delivered power [13]. Overall, this is achieved by altering the phase and direction of the reflecting signals from the surface, as shown in Fig. 2. Additionally, they can be used for enhancing network capacity and coverage area through beamforming and resource management. All these possibilities combined with what the recent fast ML/AI algorithms, RIS presents immense opportunities for performance enhancement in wireless networks. Given that every communication generation comes with a higher data demand, requiring more energy, the usage of RIS is inevitable for environmental reasons in addition to user satisfaction.

RIS can be categorized under various different classes [14], based on their design, such as i) material (metamaterial or patch-array), ii) tuning mechanism (electrical, mechanical, or thermal), and iii) energy consumption (passive-lossy, passive-lossless, or active). Each of these RIS types can be used for enhancing a different part of a communication system.

Novelty of Proposed Approach over State-of-the-art: Though digital twin applications on vehicular networks are emerging, the existing literature does not consider integrating RIS into the vehicular context of digital twins. In this paper, we propose a framework for programmable BS and RIS for vehicular networks in digital twins.

III. Proposed Framework

A. Obstacle Detection

The obstacle detection algorithm, PointPillars [5], is an on-board module that uses LiDAR data, which is also collected on-board. In this paper, we utilize the LiDAR portion of the FLASH dataset and the PointPillars 3-D object detection model to i) identify, ii) locate, and iii) determine the bounding box dimensions of the obstacle vehicles in the direct communication path. Although camera images that are synchronized with the LiDAR data are available, for simplicity we choose to utilize LiDAR only.

B. Invoking Digital Twin

Upon obstacle detection, the subject car notifies the BS it is connected to, using the standard in operation. This notification includes the relative distance coordinates between Tx-Rx and the bounding box dimensions, which were indicated above. The notification triggers the digital twin that is deployed at the edge or cloud server of the BS in our proposed scheme. A major component of a digital twin in our context is map. Since the location of the BS is set, the BS already has the local map, Tx location, and material properties for the surrounding buildings. Thus, after the digital twin is triggered, it places the detected obstacle on the fly to run ray tracing simulation, which in our case is Wireless InSite [7].

It is worth noting that a twin's performance is affected by the level of detail in i) map precision and ii) wireless parameters. Map detail includes precision in geometry and reflective surface material properties, which are available today, e.g. *OpenStreetMaps*. Wireless details include the number of allowed ray reflections, penetration through walls, and diffractions, which grow the computation burden. The trade-off between i) and ii) can be decided based on the target performance of the twin and computation resources.

C. Initial Decision-making at the Digital Twin

Once the ray-tracing is complete, the digital twin is able to make a decision as to which combination of the following wireless parameters to suggest to the real-world BS: P_{Tx}, communication standard, channel frequency, antenna pattern, and antenna directivity. Depending on the desired precision and time flexibility, the decision could be made using a simpler ML/AI algorithm deployed at the BS itself, or, if the standard is set to be 5G, O-RAN's powerful near-RT RIC component that can potentially host many xApps could be utilized for faster and more accurate results [3].

Additionally, the digital twin needs to make a decision on whether changing wireless parameters is sufficient or the support of RIS is required to achieve the target QoS at the Rx. For this, additional ray-tracing simulations might be needed to set the reflective properties of RIS, i.e. modification in phase, θ, and reflection direction, ρ. In such cases, more powerful computation resources might be needed, shifting the standard decision towards 5G O-RAN to utilize near-RT RICs. Among the aforementioned decisions, the antenna pattern and antenna directivity have a direct impact on the settings, hence performance, of the RIS we propose using. There are already fast beam steering implementations [15] that enable changing beam directions, fitting our proposed method of RIS usage.

Once the complete decision is made within the digital twin, it is sent to the subject car using the current LOS settings so that when the subject car enters the NLOS region the Rx can update its settings accordingly. Given the fact that PointPillar is able to detect obstacle at a distance, there should be sufficient time for BS and Rx.

D. Improved Decision with Intelligent Surfaces

As indicated before, RIS are capable of altering the phase and direction of the reflecting signal for targeting a specific location or constructive signal addition. Accordingly, in Fig. 2, the incoming signal follows the solid path rather than the dashed path that corresponds to the reflecting signal if the surface was not engineered. In our proposal, we have invaluable location information from the LiDAR data and the subject car's speed. Also, the LiDAR-based vehicle detection runs continuously, which allows us to predict the speed of moving vehicles. This way, the timing of the NLOS case can be predicted at the BS and the RIS configurations can be arranged in a way that the beams emitted from the BS add constructively at the Rx. We envision that the RIS are connected to the BS via cables in order to eliminate possible communication disruption between BS and RIS.

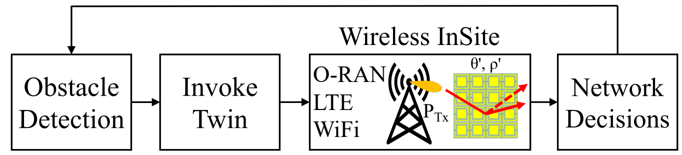

Fig. 2: Flowchart of the proposed model, where the digital twin reconfigures BS settings and RIS parameters to mitigate QoS drop in NLOS scenarios.

IV. Experiment Design: Maintaining LOS QoS in Digital Twin

A. Real-world: Creation of Ground Truth

Our ground truth is taken from the FLASH dataset [6], which is a multimodal dataset comprising GPS, camera, and LiDAR data for beam selection in vehicular networks that are collected with on-board sensors of an autonomous vehicle in an urban valley environment. We opt for the LiDAR point clouds ($10\,\mathrm{Hz}$ data rate) to detect obstacles due to its ability to precisely map surroundings in 3-D with larger field of view. The scenario we employ consists of a combination of three stationary obstacle locations with respect to the BS (*Left*, *Front*, *Right*), and two subject vehicle speeds ($15\,\mathrm{mph}$, $20\,\mathrm{mph}$), making the total number of cases six, where each case has 10 episodes. The pretrained PointPillars training set is not the FLASH dataset, so it lacks ground truth labels. To partially automate the labelling process for retraining, we used MATLAB's `LiDAR Toolbox` and predicted cars via the pre-trained PointPillar detector [5]. By comparing the predictions with the camera images, we manually finalized labels to fine-tune the model for our environment.

B. From Real-world to Digital Twin: LiDAR-based Obstacle Detection and Localization

The LiDAR sensor is placed on top of the self-driving car, becoming the origin point. We fine-tune the pre-trained model's hyperparameters, e.g. batch size, learning rate, number of epochs, using Adam optimizer. The PointPillar detection model produces results, which are depicted in Fig. 3, for each LiDAR frame in the format of $[x, y, z, d_x, d_y, d_z, \phi, \omega, \psi]$, where (x, y, z) are the centroid coordinates of the bounding box for the detected car with respect to the origin. The bounding box dimensions are given by (d_x, d_y, d_z), corresponding to length, width, and height, respectively. (ϕ, ω, ψ) correspond to the orientation angles. In our analysis, we use $d = \sqrt{\Delta x^2 + \Delta y^2}$ for distance between the origin and the detected car.

C. Digital Twin Setup in Wireless InSite

1) Initial Twin Creation: An outdoor virtual world creation for a digital twin starts from making a map that is an appropriate representation of the real world. Accordingly, we obtained the map of the experiment location from *OpenStreetMaps*, which we then processed in *Blender* to use it in Wireless InSite, making sure that building and road dimensions, material types, and foliage are a good match with their real-world counterparts. In reality, objects have many reflective surfaces, which puts a computation burden, without helping with the ray-tracing results. The effects of these reflective surfaces are rather addressed by reflection coefficients through previous publications.

The subject car's trajectory is the opposite lane of the vehicle obstacle. We model the obstacle car (2018 Toyota Camry) as a metal box with the dimensions of $1.84m \times 4.88 \times 1.44m$, by reading them from the car's specifications. We placed the BS location in a way that its location relative to the surrounding buildings matches with the real world. The height of the BS is $0.95\,\mathrm{m}$, following the FLASH dataset [6], which we use to evaluate the performance of obstacle detection. We used directional antennas for RIS experiments, whereas for the rest of the experiments we used half-wave dipole antennas for implementation convenience. We selected the propagation model in the Wireless InSite to be *X3D*, as it is the most comprehensive one. The number of allowed reflections and diffractions are 3 and 1, respectively.

2) Running the Twin: Upon obstacle detection, the digital twin automatically places the obstacle on the fly using the PointPillar algorithm's output. This is followed by running ray-tracing, which determines P_{Rx} values at the subject car's trajectory. Then, the digital twin calculates P_{Tx} level that will achieve the same P_{Rx} values as in the LOS case. Once the rays are determined, the effect of the rest of the wireless parameters could be calculated. There are a number of wireless metrics to change, which collectively make up many combinations. Deciding the best wireless parameters could be done using deep learning techniques.

3) Running the Improved Twin: Among the decisions of the deep learning model, deciding whether using RIS will further improve the received power is the triggering factor for RIS. Once this is decided BS reconfigures antenna beams and the reflective parameters of the RIS so that the emitted signals are added constructively at Rx.

V. Performance of the Proposed Digital Twin

A. Evaluation Metrics

Our evaluation consists of three parts. First, we evaluate the performance of the obstacle detection using recall scores. Second, we make analysis for P_{Tx} needed to achieve the same level of P_{Rx}, which we refer to as QoS, when we only reconfigure the BS. Lastly, in addition to the BS reconfiguration, we also reconfigure the RIS for P_{Tx} analysis. For the second and third evaluation methods, we test two wireless standards, namely LTE and 802.11ac, over different obstacle distances.

B. Performance of the Obstacle Detection Module

For generating this set of results, we choose transfer learning approach, taking a baseline PointPillar model [5] and adapted it to our distribution. We divided our dataset into 70% training and 30% testing, assigning fair representation to each sub-category, and used grid search for fine-tuning the model. We select recall as an evaluation metric to quantify the error due to missing predictions by comparing it with the accurately labelled ground truth samples. Fig. 4 compares the recall scores from each sub-category and average recall is 73.46%.

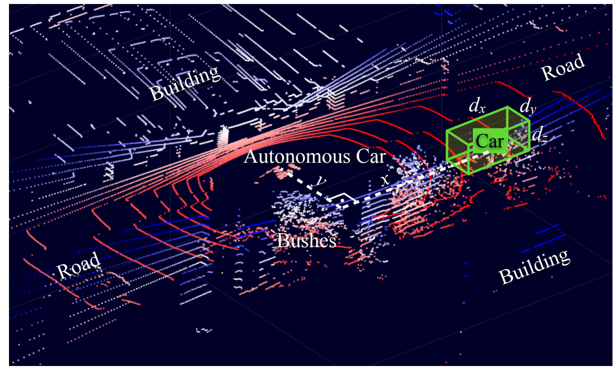

Fig. 3: A sample output of obstacle detection using finetuned PointPillars [5] and the FLASH dataset [6]. The autonomous car is displayed at the center (black region with an automobile silhouette) and the detected car as a green bounding box. The outputs from PointPillar and the surrounding labels are displayed in bold white for visual presentation, where $\phi = \omega = \psi = 0$.

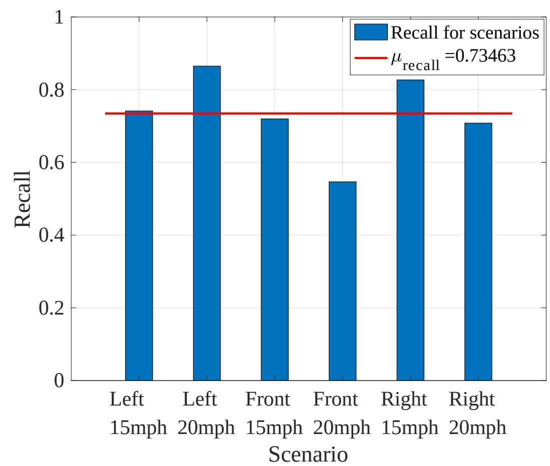

Fig. 4: Recall plot for object detection using finetuned PointPillars [5].

We observe average maximum distance from which an obstacle can be detected is $11\,\mathrm{m}$ allowing for sufficient time to perform further steps. When obstacle and vehicle are parallel distance eventually reduces to $5.3\,\mathrm{m}$. The middle plot in Fig. 5 exemplifies distance change over time samples for a typical episode. $\mu_{(d_x,d_y,d_z)} = (1.94, 4.64, 1.67)$, μ indicating average, which slightly deviates from the real obstacle dimensions. Thus, for our ray tracing experiments, we used the real dimensions.

Inference: The adapted PointPillar algorithm yields an average recall of 0.73 on the FLASH dataset, while deviating only $19cm$, on average, from the real obstacle dimensions. This allows more precise ray-tracing, hence P_{Tx} allocation, through digital twins when an obstacle is detected.

C. Performance Gain by Reconfiguring BS Parameters

We provide the P_{Tx} analysis to achieve the same level of P_{Rx} over different distances, d, and communication standards when only the BS is reconfigured in the top plot in Fig. 5. The distances between the detected car obstacle and the subject car are displayed in the middle plot, with x-axis displaying time stamps of the $10Hz$ sampling rate for LiDAR data. The

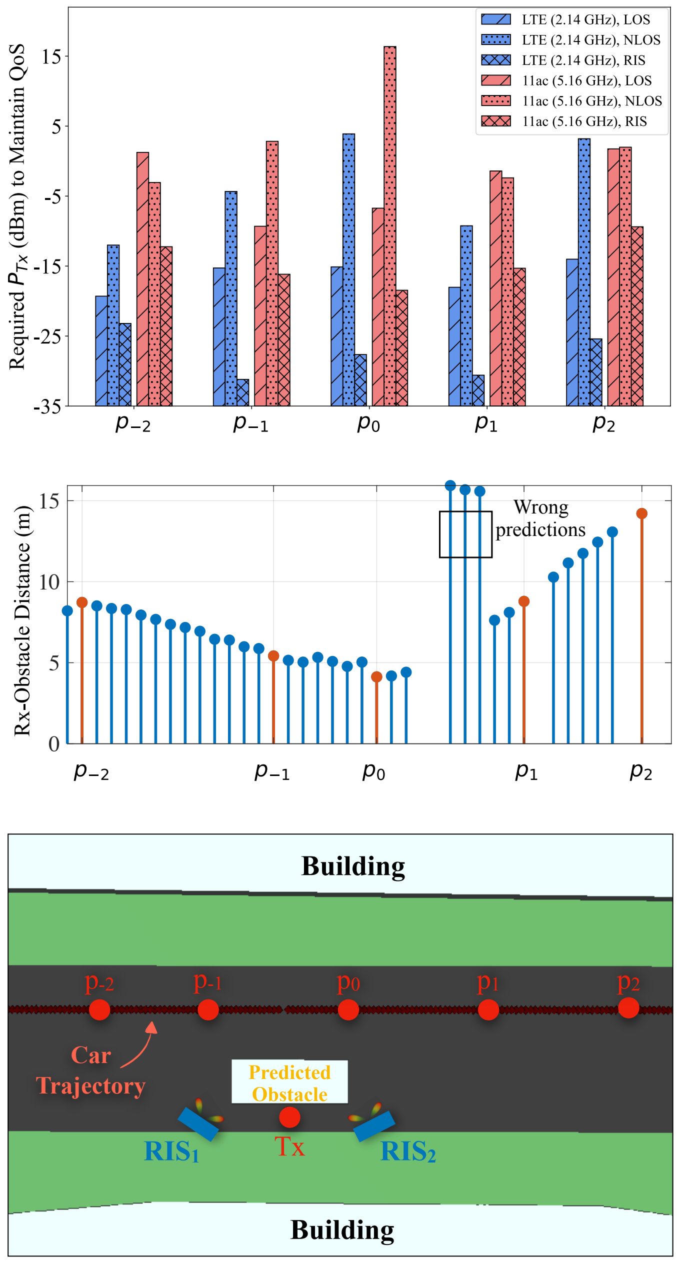

Fig. 5: Required P_{Tx} to maintain the signal level at $-65\,\mathrm{dBm}$ (high QoS level) at different sample points on the subject car's trajectory (top), predicted distances between the subject car and the obstacle (middle), digital twin with sample points displayed (bottom). The use of RIS always outperforms LOS case in terms of required P_{Tx}.

bottom picture consists of multiple snapshots of the Rx on the subject car along with the Tx, vehicle obstacle, and RIS in the digital twin, which are all created in Wireless InSite. The snapshot locations are labeled as p_{-2}, p_{-1}, p_0, p_1, p_2, which are displayed in every plot in Fig. 5. The figure is from the scenario of *Front-15 mph*. In our analysis, we vary P_{Tx} in a way that P_{Rx} at every sample point on the car trajectory is $-65\,\mathrm{dBm}$, which is labeled as an excellent signal level.

It is evident from the top plot in Fig. 5 that required P_{Tx} for excellent signal level in NLOS cases are much higher compared to the LOS, because of the lack of direct communication links and received signals having to travel more, undergoing more attenuation. The Tx compensates this with higher transmit power. We select the LTE and 802.11ac signal frequencies, f_c, to be $2.14\,\mathrm{GHz}$ (band 1) and $5.16\,\mathrm{GHz}$ (channel 32), respectively. When we compare the LTE and 802.11ac standards, we observe that LTE requires less power due to operating in lower frequency, which causes less attenuation as signals propagate over the air.

Inference: Determining optimum P_{Tx} is beneficial and important, because excessive transmit power could be a method to mitigate the QoS drop in NLOS case, which comes with extra energy cost. Contrarily, if P_{Tx} is underestimated, QoS is sacrificed or even lost. Using digital twins, optimal P_{Tx} values could be reliably calculated. We show that even with configurable BS, required P_{Tx} is $18\,\mathrm{dBm}$ higher in NLOS, on average.

D. *Performance Gain by Reconfiguring BS and RIS Parameters*

For this P_{Tx} analysis, the experiment setting is the same as we described previously, except this time we direct transmitted power to RIS using directional antennas, where both the E and H-plane half-power beam widths are $15°$. Then, RIS reflects these incoming beams to the target destination. We use two RIS located on the same side of the Tx, which are shown on the bottom figure in Fig. 5 and depending on the target location we active only one RIS. Evident from the top figure, the use of RIS consistently requires lower P_{Tx} from the Tx compared to both only BS configuration (NLOS scenario) and LOS scenario. In fact, compared to the LOS cases, RIS reduces the required P_{Tx} $-16.3\,\mathrm{dBm} \rightarrow -27.6\,\mathrm{dBm}$ and $-2.9\,\mathrm{dBm} \rightarrow -14.3\,\mathrm{dBm}$ for LTE and 802.11ac, respectively.

RIS provides more efficient use of the transmitted power. The rays emitted from the BS that are not directed to the target will be lost, but with the usage of data-driven antenna directivity and RIS, we utilize the power which otherwise would be wasted. We simulate the improvement from RIS in Wireless InSite following an ad-hoc approach, meaning we place one transmitter at each RIS location and let these transmitters emit the same power level as the delivered power from the BS at RIS locations using directional antennas.

Inference: Using digital twin supported reconfigurable RIS, we achieve $2.32\times$ less P_{Tx} in dBm, on average, even in NLOS between the BS and Rx.

VI. Future Directions and Challenges

The concept of digital twin and RIS is still at nascent stage and integrating that into the connected and autonomous vehicles bring a number of challenges and open problems.

- Vehicle-to-everything (V2X) networks require updated infrastructure that should be easy to deploy at low cost. Given that O-RAN deployment proposals rise [1], the flexibility and multi-vendor interoperability of O-RAN could be a solution for lowering deployment and operational costs.
- Interconnected components in V2X might expose security and privacy vulnerabilities. However, security measures are already under development for O-RAN [3].

- In this paper, we only use LiDAR data for obstacle vehicle detection. For the future work, we aim using multimodal data, e.g. camera and LiDAR, to make more robust detections.
- High computing sources [12] and efficient algorithms [9] are vital for timely decisions in fast-pacing V2X networks. A quantitative trade-off analysis between computation burden and acceptable sacrifice, e.g. wrong obstacle detection vs. QoS gain/loss vs. consumed power, will determine priorities.
- As real life RIS implementations that support multiple operation frequencies emerge, we plan expanding our simulation into real RIS implementation and dynamically configuring RIS and BS resources through reinforcement learning within digital twins.

VII. Conclusions

We propose a digital twin framework for connected and autonomous vehicles with the goal of bettering QoS during inherent NLOS cases in dynamic vehicular networks using programmable BS and RIS. The workflow of our method starts with obstacle detection using a set of vehicle-mounted LiDAR sensors and a detection module, which notifies the BS the autonomous vehicle is connected to about the obstacle, providing the location and dimensions information. Then, the digital twin, deployed at the BS, is triggered and runs ray-tracing to determine optimum BS settings, e.g. transmit power, communication standard, antenna directivity, whether to utilize O-RAN's computing sources, and RIS parameters, reflection and phase modification, that will mitigate the QoS drop when no direct communication is possible for the autonomous vehicle. We tested the feasibility of our framework using real life LiDAR data for obstacle detection and Wireless InSite for digital twin evaluation. We show that using RIS allows reducing transmit power by $2.32\times$, on average in dBm, compared to the LOS scenarios during even NLOS cases between the BS and Rx.

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