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A Comprehensive Review of Path Loss Prediction Methods and Models of Vehicular to Infrastructure (V2I) Communication

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Abstract: Vehicle-to-Infrastructure communication is a key enabler of Intelligent Transportation Systems, supporting traffic efficiency and road safety. However, accurate path-loss prediction remains challenging due to dynamic urban propagation conditions, frequent non-line-of-sight situations, mobility, and heterogeneous roadside deployments. This paper presents a comprehensive review of V2I path-loss prediction methods, encompassing classical empirical and semi-deterministic models, as well as modern artificial intelligence approaches, including machine learning and deep learning. We summarize the main modeling assumptions, required inputs, strengths, and limitations across different environments and frequency bands, and we highlight recent trends such as hybrid physics-guided learning, data-driven feature engineering, and interpretability tools. Finally, we discuss open research challenges and future directions toward robust, generalizable, and practical V2I path-loss modeling.

Keywords: Path Loss Prediction; Vehicle-to-Infrastructure (V2I); Empirical models; Machine Learning; Deep Learning; Multi-modal Sensing; mmWave; DSRC/C-V2X

Table 1: Some abbreviations with their descriptions

Abbreviation	Full Term
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2P	vehicle-to-pedestrian
V2X	Vehicle-to-Everything
PL	Path Loss
LOS	Line-of-Sight
NLOS	Non-Line-of-Sight
DSRC	Dedicated Short-Range Communications
RSU	Roadside Unit
OBU	Onboard Unit
3GPP	3rd Generation Partnership Project
ITS	Intelligent Transportation Systems
ML	Machine Learning
DL	Deep Learning
ANN	Artificial Neural Network
MLP	Multi-Layer Perceptron
LSTM	Long Short-Term Memory
LiDAR	Light Detection and Ranging
mmWave	millimeter-wave
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
R^2	Coefficient of Determination

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1. Introduction

V2X technology has transformed vehicles into intelligent, networked systems enabled by rapid advances in electronic information technologies [1], [2]. V2X mainly includes V2I and V2V communications, which support information exchange between vehicles and surrounding entities to improve coordination and situational awareness [3]. The general V2X concept is illustrated in Fig. 1 [4].

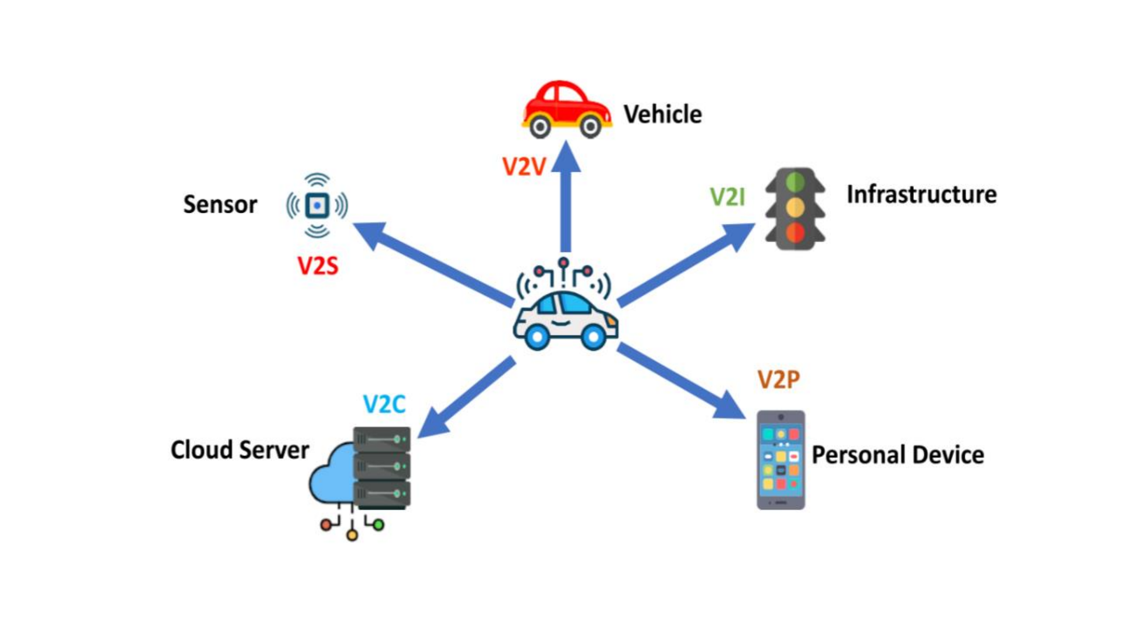


Fig. 1. Conceptual illustration of V2X communications, highlighting V2I and V2V links [4].

V2I communication specifically refers to wireless interaction between vehicles and roadside infrastructure such as traffic lights and control facilities, as shown in Fig. 2 [5].

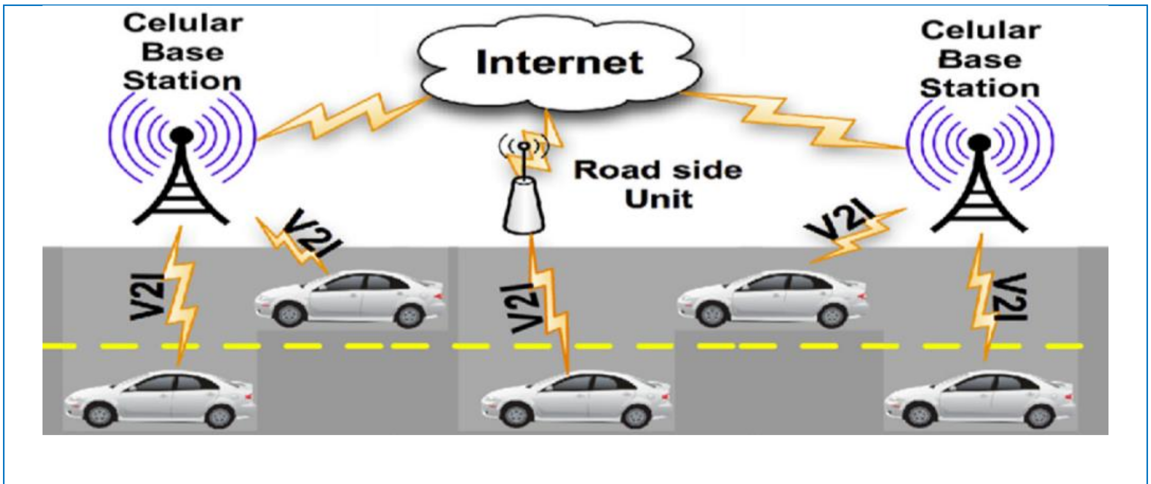


Fig. 2. General V2I system architecture showing vehicles equipped with OBUs communicating with RSUs, such as traffic lights and control facilities, with connectivity to back-end ITS Services [5].

V2I is a key component of Intelligent Transportation Systems (ITS) and can enhance traffic management by reducing fuel consumption, waiting time, and travel delays under dynamic conditions [6].

Depending on application requirements, V2I systems may rely on cellular technologies and short-range wireless solutions such as Wi-Fi, WiMAX, Bluetooth, ZigBee, and DSRC; these enabling technologies are summarized in Fig. 3 [7].

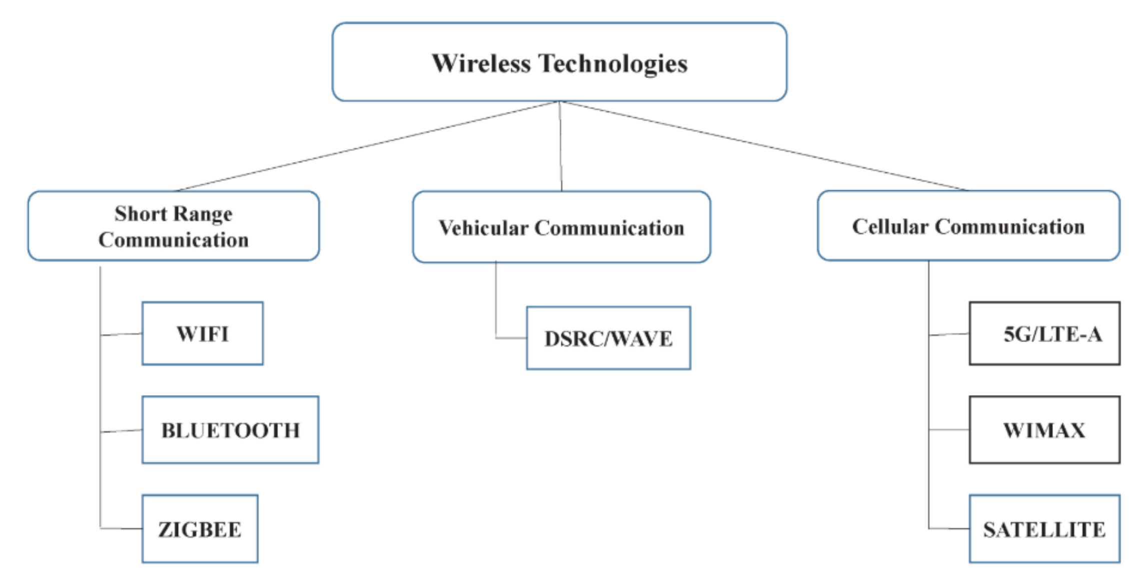


Fig. 3. Common communication technologies enabling V2I/V2X services (short-range and cellular-based options such as DSRC/IEEE 802.11p and cellular V2X/5G, alongside complementary wireless technologies) [7].

In vehicular networks, supporting hardware platforms, including sensors and embedded devices, are crucial for the practical deployment of safety-oriented services [8]. Enhancements in communication protocols, such as extensions to IEEE 802.11p and priority-based MAC designs, aim to bolster data delivery, reduce latency, and improve reliability [9], [10], [11], [12]. Although heterogeneous networking (Het-Net) aids coverage, its handoff behavior may restrict effectiveness in time-sensitive security applications. However, it is valuable for data collection and acts as a safety services backup [13]. Additionally, V2I performance has improved through various algorithms, including RSU-assisted broadcast schemes and mobility-aware handover optimizations [14], [15].

Accurate PL modeling is vital for the design and optimization of V2I communication systems, as PL is influenced by multiple factors such as free-space loss, reflection, diffraction, refraction, scattering, and absorption [16], [17], [18], [19]. The complexity of predicting PL in vehicular scenarios surpasses that in traditional cellular environments due to low antenna heights and user mobility[20][21],[22]. Field measurements highlight the significant impact of vegetation and urban obstructions on received power in V2I links, especially in micro-cell scenarios at frequencies like 2.4 GHz. A number of studies focus on the 5 GHz band, factoring in Doppler effects, line-of-sight (LOS) versus non-line-of-sight (NLOS) conditions, and antenna height [23],[21], [22], [24]. Classical empirical models (Hata, COST-231, Walfisch–Ikegami, SUI, and Ericsson) have been analyzed for their performance across various frequency bands, revealing variability influenced by environment and frequency [25].

Recently, ML and DL techniques have emerged for predicting PL in vehicular channels, facing challenges like interpretability and computational costs [26]. New architectures are examining DSRC and millimeter-wave communications, integrating learning-based decision methods such as TOPSIS and reinforcement learning [27]. Research indicates ML can capture the correlation between PL and environmental factors in urban V2I contexts, supported by extensive measurements[28]. Moreover, multimodal sensing frameworks that combine diverse inputs have been proposed to enhance robustness under different conditions, with suggestions for refinement to improve urban PL prediction [29].

Contributions and Novelty: To clarify the scope and contributions of this review, the main contributions

are summarized as follows:
i-Proposes a unified taxonomy of V2I path-loss prediction approaches (empirical, deterministic, ML, DL, and multimodal fusion) to enable consistent comparison across studies.
ii-Consolidates key study attributes into a unified comparison template (frequency, scenario, inputs, dataset type, and metrics), clarifying sources of inconsistency in reported results.
iii-Synthesizes practical drivers of V2I path loss prediction (e.g., distance dominance, impact of antenna height, and value of contextual/environmental descriptors).
iv-Highlights open research gaps and provides actionable directions toward reproducible benchmarking, interpretability, and real-world validation.

Therefore, this paper reviews the literature on PL prediction for V2I communications. The remainder is organized as follows: Section 2 summarizes V2I channel characterization and PL prediction models, and Section 3 concludes the review.

1.1 Review Methodology

The methodology of this review was a focused narrative-systems approach to gathering and analysing literature. For the compilation of literature, three databases were used: IEEE Xplore, Scopus, and Google Scholar. The articles identified in each of the databases were searched using the following combinations of keywords: "V2I path loss", "Vehicle-to-Infrastructure", "V2X propagation", "DSRC 5.9 GHz", "machine learning path loss", and "deep learning path loss". All searches were carried out looking primarily at the peer-reviewed literature from 2015-2025 and to a small extent the foundational literature on Empirical and Model Reference Propagation. Only studies that: (i) dealt with V2I or closely related to V2X, (ii) provided a clear PL model/predictor with clearly identified inputs (e.g., distance, frequency, antenna heights, environment), and (iii) provided quantitative validation (either through measurement or simulation) using common metrics (e.g., RMSE/MAE/R^2) or parameter estimates (e.g., path-loss exponent) were included in this review. The resulting papers were compiled and synthesized into a taxonomy of empirical, deterministic, ML, and DL, with each paper summarized using a common template that included frequency band, scenario type, key inputs, dataset origin, and limitations.

2. An overview of V2I Channel Characterization and the path loss prediction models

In this portion of the article, essential attributes of the V2I channels and characteristics related to these channels at scale are summarized, followed by a review of the PL prediction model family classes. The overview is from the classical empirical methods towards newer generation ML and DL approaches, indicating the circumstances within which each class is the most appropriate.

2.1 V2I Channel Characterization

To inform future model selection and comparison for Vehicle-to-Infrastructure (V2I) communications, this review highlights key characteristics of V2I propagation channels. Accurate modeling necessitates a realistic understanding of wireless channel properties, especially in urban settings where unique environmental factors like topography and obstructions affect link reliability. Previous research utilizing three-dimensional propagation modeling has assessed factors such as received signal strength, RMS delay spread, and Doppler shift at 5.9 GHz. Findings from a study in a metropolitan area indicated significant statistical variation in channel path loss, with environmental aspects like nearby trees causing quasi-LOS conditions and buildings leading to pronounced NLOS blockage. Overall, the established channels showed limited consistency in measurements over time.

The Doppler effect in V2V and V2I communications at 5.9 GHz is discussed in [21], emphasizing that higher vehicle speeds increase Doppler spread and cause faster channel variations, which complicates

reliable link design. The Doppler frequency f_d (Hz) between the transmitter (Tx) and receiver (Rx) can be expressed as [21]:

$$f_d = (\frac{v}{C_0}) \cdot f_0 \cdot cos(\alpha) \quad (1)$$

where v is the relative velocity between Tx and Rx (m/s), C_0 is the speed of light (m/s), f_0 is the carrier frequency (Hz), and α is the angle between the relative motion direction and the direction of arrival of the propagation path under study [21].

Complementary measurement-based characterization is provided in [30] , which analyzes V2I propagation channels and classifies links into LOS-below (LOS-B), NLOS, and LOS-above (LOS-A) categories. The study investigates large-scale fading effects (shadowing) and the path loss exponent, and reports that the proposed path-loss model achieves a reasonable goodness-of-fit, with mean estimation error close to zero and reasonable standard deviation, supporting its use for test design and performance assessment in V2I systems [30].

In addition, [31] discusses heterogeneous vehicular networking (HetVNET) that integrates DSRC and Long-Term Evolution (LTE), see Fig. 4, highlighting their complementary trade-offs: LTE provides wider coverage but may be less efficient for strict real-time requirements, whereas DSRC supports low-latency communication but typically has a shorter range. The paper also emphasizes practical channel challenges such as fading, multipath, congestion, and deployment constraints near roadways and intersections.

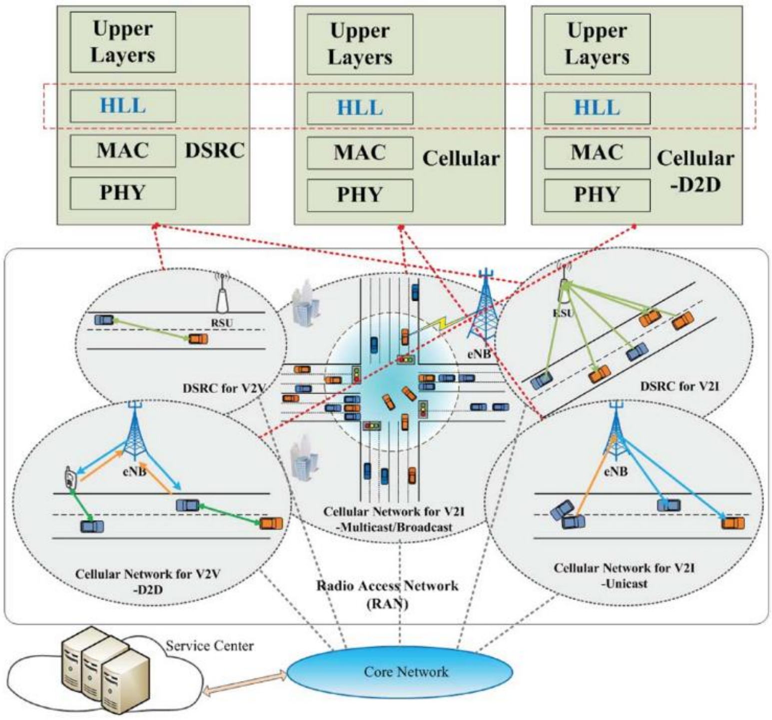


Fig. 4. Example of a unified (HetVNET) architecture integrating DSRC and cellular (LTE) connectivity to support V2I services under different coverage/latency requirements [31]

Reference [23] has investigated the effects of buildings as obstructions on V2I links in a setting resembling a microcell. They used static LOS measurements at a frequency of 2.4GHz with an IEEE 802.15.4 device to validate several well-established path-loss models and determined that the presence of typical residential building obstructions had considerably varying impacts on received power and therefore emphasized the importance of comparing their measurement results with well-known baseline path-loss models such as free-space loss or log-distance models. They also indicated in their paper that future studies should investigate additional impacts such as variable antenna height, frequency dependency, and more varied NLOS measurements. To assist readers in finding relevant channel conditions and parameters for V2I modelling, refer to Table 2, which is a summary comparison of all the reviewed literature related to channel characteristics.

Table 2: Summary of key V2I channel characterization studies, including frequency band, scenario, channel focus (e.g., Doppler, LOS/NLOS, fading), and the main takeaway relevant to Section 2.1.

Ref.	**Study type**	**Frequency**	**Scenario**	**Channel focus**	**Data**	**Key takeaway for Sec. 2.1**
[21]	Simulation/ analysis	5–5.9 GHz	V2I & V2V, 15–1000 m; up to 200 km/h	Doppler + multipath impact	Simulated channel scenarios	Mobility induces fast time-variation (Doppler), complicating PL/channel modeling.
[30]	Field measurements	2.4 GHz	V2I with vegetation/ obstructions	LOS/NLOS classes; large-/small-scale fading (PLE, shadowing, K-factor)	Extensive measurements + Model validation	Provides measurement-based channel parameters and link classes useful for PL modeling and design.
[31]	Survey (networking)	DSRC + LTE (HetVNET)	ITS services on heterogeneous networks	Network-layer context (QoS, access, handover challenges)	Literature survey	Motivates why the channel variability + QoS/handover constraints matter in V2I deployments.
[23]	Field measurements	2.4GHz (IEEE 802.15.4)	Residential microcell; LOS with building blockage	Obstruction impact on RSSI/ PL; model validation	Real RSSI measurements + best-fit PL model	Confirms blockage effects and the need to validate PL models under realistic obstructions.

2.2 Path Loss Prediction Models

This part examines various examples of PL predictions for vehicle- based channels; these predictions are evolving from the traditional means of predicting PL, such as using empirical processes and deterministic models, to methods that are based on ML and DL. The review also aims to illustrate the assumptions made during modelling, including the operational context (frequency/environment), necessary input variables, and performance metrics, to create opportunities for fair comparisons of PL prediction models developed by several different researchers/engineers.

2.2.1 Logarithmic distance and Two-ray based models

Using existing channel characteristics for channel characterization, empirical PL models are still very popular due to their ease of use, interpretability, and ability to be used to set typical or baseline levels for planning and deployment. The authors in [32] Compare multiple experimental PL models (T1-T4) against the log-distance PL Model for their comparative accuracy using different measures, including MAPE, MSE, and RMSE. They conclude that the best-performing model is dependent on the configuration of the paths used in that particular scenario, while obstruction effects have a significant negative effect on V2V relative to V2I for all the configurations of test points.

In [33], field measurements were taken to study V2I PL measurements at 700 MHz and 5.9 GHz in a dense urban environment. Based on a logarithmic transformation of the loss models, the loss model exponent was calculated using a least-squares fit between the PL and height of various Tx antennas for each configuration. The study found that the loss exponent values for various configurations varied by antenna height and frequency, about path loss; lower frequency (700 MHz) tended to have lower losses and better propagation than the higher frequency (5.9 GHz); see Figs. 5 and 6:

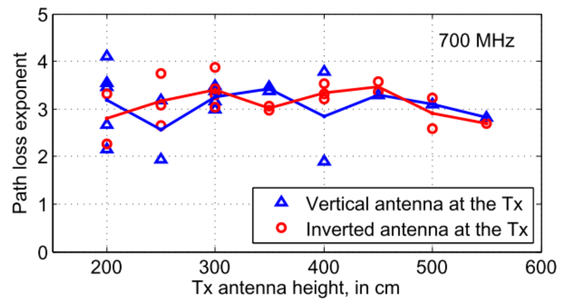


Fig. 5. Path-loss exponent versus transmitter antenna height for dense-urban V2I measurements at 700 MHz [33].

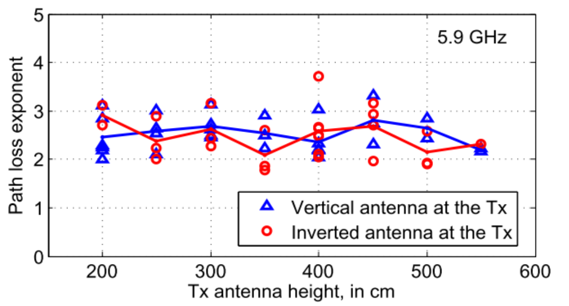


Fig. 6. Path-loss exponent versus transmitter antenna height for dense-urban V2I measurements at 5.9 GHz [33].

In [22], The Two-Ray Ground Reflection and Log-Distance models were used to perform a study of V2I performance at 5.9 GHz in urban/suburban environments, factoring in antenna height and distance (1.5 m - 3.5 m) and range of placements (50-300 m) for both urban and suburban cases (1.5% and 2.5%). The results of this study demonstrated that by increasing the height of the Tx antenna from a height of 1.5 m to 3.5 m, there was a measurable increase in the performance of the communication link when the configuration of the Tx antenna height was near/medium distance. The Log-distance path loss model can be expressed as [22]:

$$PL(dB) = PL(d_0) + 10\gamma\, log_{10}\left(\frac{d}{d_0}\right) + X_\delta \tag{2}$$

where d and d_0 are in (m), γ is the path-loss exponent, and $PL(d_0)$ is the intercept value of the path loss model at the reference distance d_0, and X_δ is a zero-mean Gaussian random variable (shadowing) in (dB) [22]. Since this review will summarize and analyze the available literature representing various types of path-loss model parameterizations, it is important to present only the representative parameter value(s) instead of simply providing a narrative description of those models. For that reason, we have collected together the results from [22] that provide estimates of Log-Distance parameters into a single table, see Table 3 for easy access to those estimates of $PL(d_0)$and γ performed at different antenna heights and in various types of environments.

Table 3 : Reported $PL(d_0)$ and γ values from measurements in [22]

	γ	$PL(d_0)$
Urban-3.5 meters	1.98	44.8
Urban-1.5 meters	1.92	45.5
Suburban-3.5 meters	1.12	66.3
Suburban-1.5 meters	1.41	60.1

2.2.2 Parabolic Equation (PE) method

Radio wave propagation modeling occurs in an urban area, but with a new study in the reference [34]. Characteristics of the V2I communication and vehicular ad-hoc networks (VANET) are studied to a lesser extent. The problem is solved for the first time using the three-dimensional bidirectional PE method. Permeable (i.e., completely electrically conducting) cuboids are used to represent the buildings and other objects of blockage. A harmonic radiator can be modeled with any directional pattern. Several propagation scenarios are numerically modeled and then compared with the ray-tracing method. The results considerably illustrate that the PE and Ray-tracing (RT) method yield near-exact results, see Fig. 7. Some recommendations are drawn from the numerical results to support the deployment of VANETs.

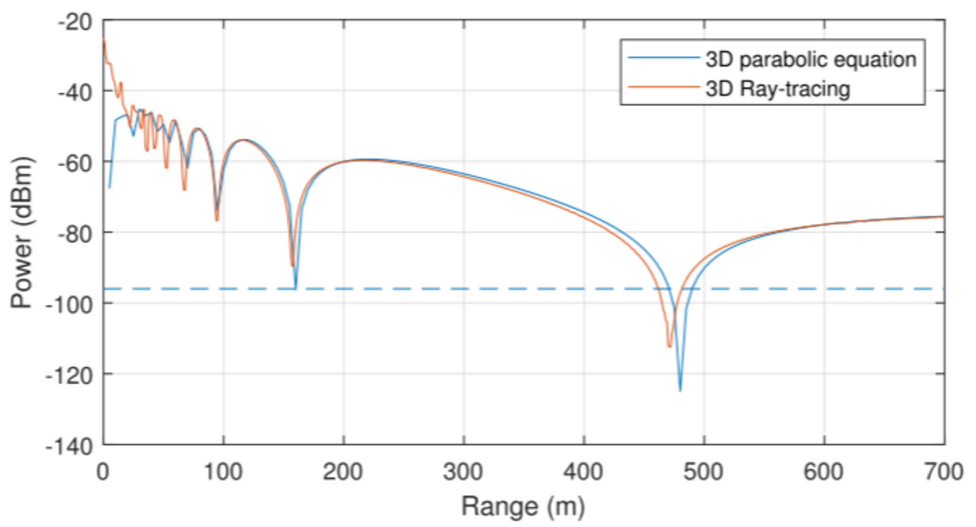


Fig. 7. Obstacle-free propagation scenario: signal-level distribution at 1.5 m receiver height, used to compare the PE-based solution with ray-tracing results in [34]

2.2.3 Visible Light Communications (VLC) method

In addition to visible light communications (VLC), an early observational study looked into V2I systems on mountain roads refer to Fig. 8 from both LOS and NLOS perspectives. The referenced study [35] considered the effects of weather (rainfall and snowfall) as well as the impact of operating in motion on the parameters of path loss, received power, channel capacity, and probability of outage, concluding that the display of significant variation in weather in that environment was less important than the vehicle transmission distance. Using some Monte Carlo simulations in MATLAB to support those suggestions, the findings yielded a reasonable path loss of -52.5 dB at 50 meters. The authors pointed out how rain and snow impact the V2V-VLC communication. Further research is needed to address the detrimental outdoor VLC propagation effects of rain/snow.

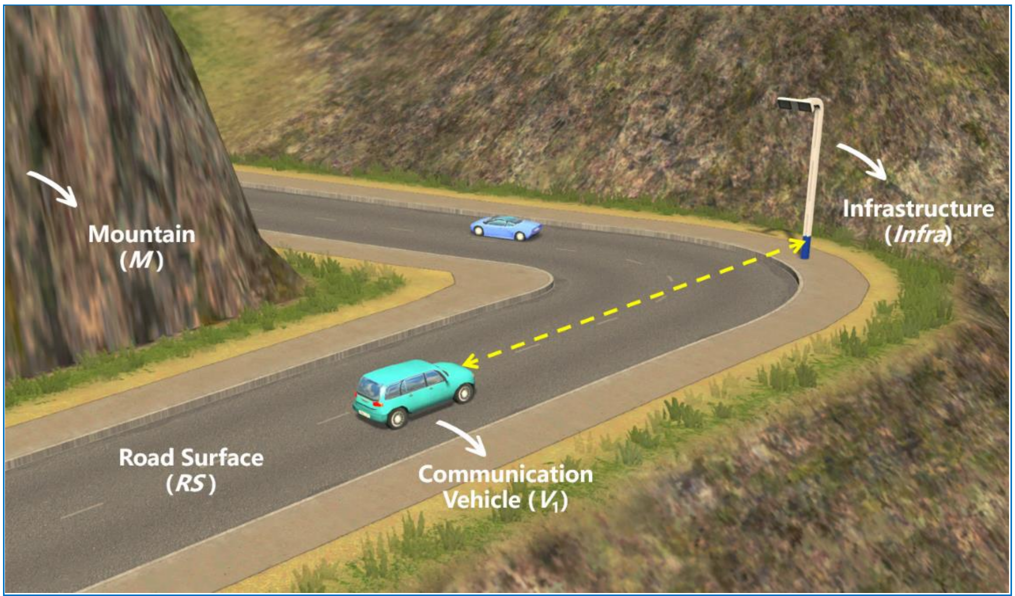


Fig. 8. Example VLC-based V2I scenario on a mountain route, illustrating LOS/NLOS operation conditions are considered in [35].

2.2.4 Machine Learning -Based Path Loss Prediction

While fixed-form model limitations must be addressed, traditional ML techniques provide an opportunity to train algorithms that accurately model and predict complex non-linear relationships between Environmental Conditions and PL from Data sets, and provide a greater degree of accuracy across a wider variety of propagation conditions than can be obtained using traditional empirical methods. In reference [36], Four ML regression algorithms (ANNs, SVMs, Random Forests (RFs), and Gradient Boosting Trees (GBT)) were evaluated for their ability to predict V2I PL using Data from Real-World Environments, and a Generalization Test was performed on the V2I PL prediction results on Data collected from several completely different spatially Unfamiliar V2I Locations. The GBT Algorithm provided Superior Prediction Quality to the Log-Distance Empirical Baseline Model, and emphasis was placed on using Contextual Features (Traffic Density, Roadway Characteristics, etc.) to improve V2I PL Prediction Performance, as well as using SHAP (Shapley Additive Explanations) for Interpretability Analysis for future research in [36].

In addition, [37] presents an overview of the characteristics of a number of different ML-based PL prediction techniques that were developed for use in the context of High-Frequency (HF) Communications in mmWave Indoor Propagation Environments, and compared to the Wall Losses models of existing empirical models developed for HF communications. In their analysis, it was noted that although ML techniques improve the Fitting of PL data compared to Existing PL Empirical Models, there are opportunities for combining and balancing the interpretability of Predictor Subsets of various ML algorithms with Prediction Accuracy.

Finally, [38] provides a Benchmarking Study of Existing V2I PL Measurement Data from Italian RSUs in Bologna, Italy, and lists ML techniques (XGB, MLP) developed and compared to Empirical Baseline Models (Dual Slope and 3GPP TR 38.901) in terms of prediction accuracy at V2I PLs of 5.9 GHz. Researchers in this study concluded that there are significant improvements associated with using ML techniques for V2I PL modeling, and the most important Factors affecting V2I PL Predictions include distance, RSU Height, and Features of the Nearby Environment. The findings emphasize how ML enhances the prediction accuracy of path loss in V2I systems under dense urban conditions, see Fig. 9.

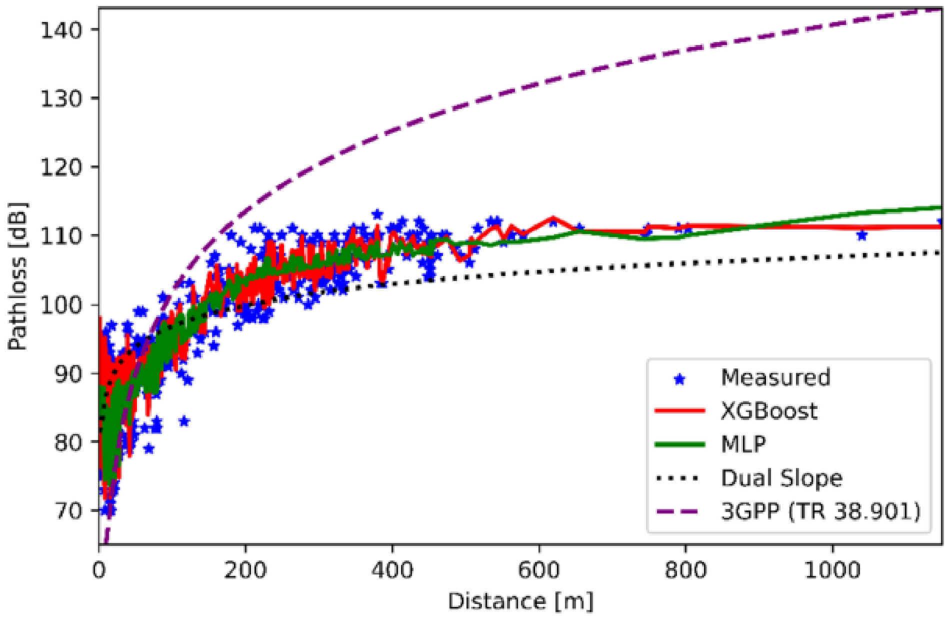
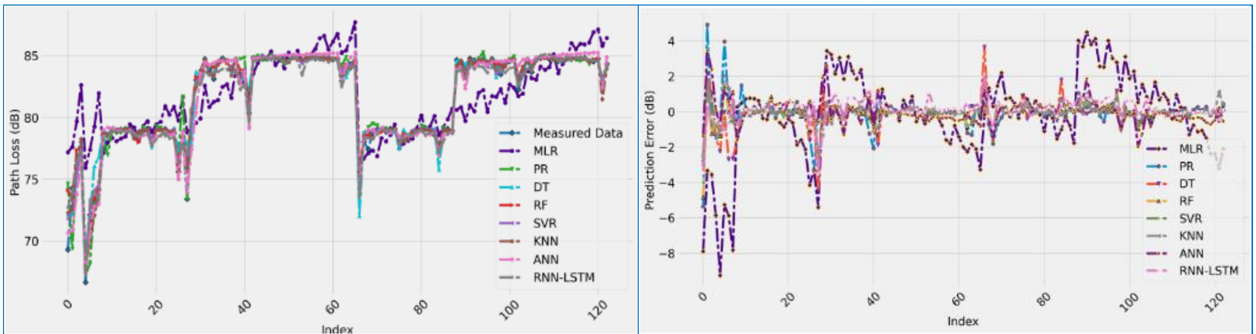


Fig. 9. Comparison between measured and predicted path loss in a dense-urban V2I dataset, illustrating the performance of baseline and ML-based models as reported in [38].

The results of the study [39] indicate that advanced neural networks have the potential to accurately replicate the behaviour of non-linear propagation (such as those created by vehicles travelling through an urban environment) if used with the correct feature sets. Likewise, selecting an appropriate feature set is equally critical in order to accurately describe the non-linear propagation behaviour that occurs between two objects in motion. In addition to the characteristics discussed above (e.g., Tx-Rx distance, frequency, antenna height, and angle of arrival), additional factors that may affect V2I propagation must be considered (e.g., Line of Sight vs Non-Line of Sight transitions, vehicle motion dynamics, urban building layouts, and vegetation). Fig. 10 shows both the actual path loss values for the measured data and the predicted path loss values from ML models, as well as the associated path loss prediction error for the evaluated models [39].



(a) measured vs. predicted path loss. (b) corresponding prediction error distribution.

Fig. 10. Performance of ML-based path-loss prediction models in [39].

The research provided in [40] is not only applicable to V2I but also has a lot of applicable methods available to use in V2I Path Loss Prediction. The methodological framework proposed uses a Data-driven method, PCA for Dimensionality Reduction, ANN/MLP Models and a Gaussian Process (GP). It is shown that PCA can reduce the dimensionality of the feature space, increase the generalization of the models developed, and significantly decrease the time required to train the networks. In relation to V2I

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Applications, this indicates that by reducing the dimensionality of the feature space to the minimum amount of redundancy while retaining only the most relevant propagation drivers, a more efficient model can be created that is appropriate for large datasets related to vehicular applications. In addition, building a Data-driven Shadowing component using Gaussian Process Variance provides a new method of capturing and representing the influence of the environment on variability (blocking and scattering) that has a particular impact when using V2I in Urban Areas and is not accounted for in traditional LOS Models.

The work in [41] extends ML-based prediction beyond PL to include packet drop (PD) and latency variations over short and long-time scales. The proposed neural-network model is evaluated in both offline and online modes and is compared against common PL estimators, including the dual-slope distance-breakpoint model, polynomial fitting, and G shadowed fading. Relative to these baselines, the NN-based approach improves the trade-off between small-scale fitting and large-scale averaging and supports near real-time regression when training data remain coherent, see Fig. 11. Building on this, an LSTM-type predictor is introduced to capture temporal dependencies and environmental influences on channel parameters. Such neural architectures are particularly relevant for realistic vehicular links, where reflections, refractions, and mobility create nonlinear and time-varying propagation behavior, suggesting potential applicability to V2I PL modeling when complemented with outdoor-specific features and scenarios.

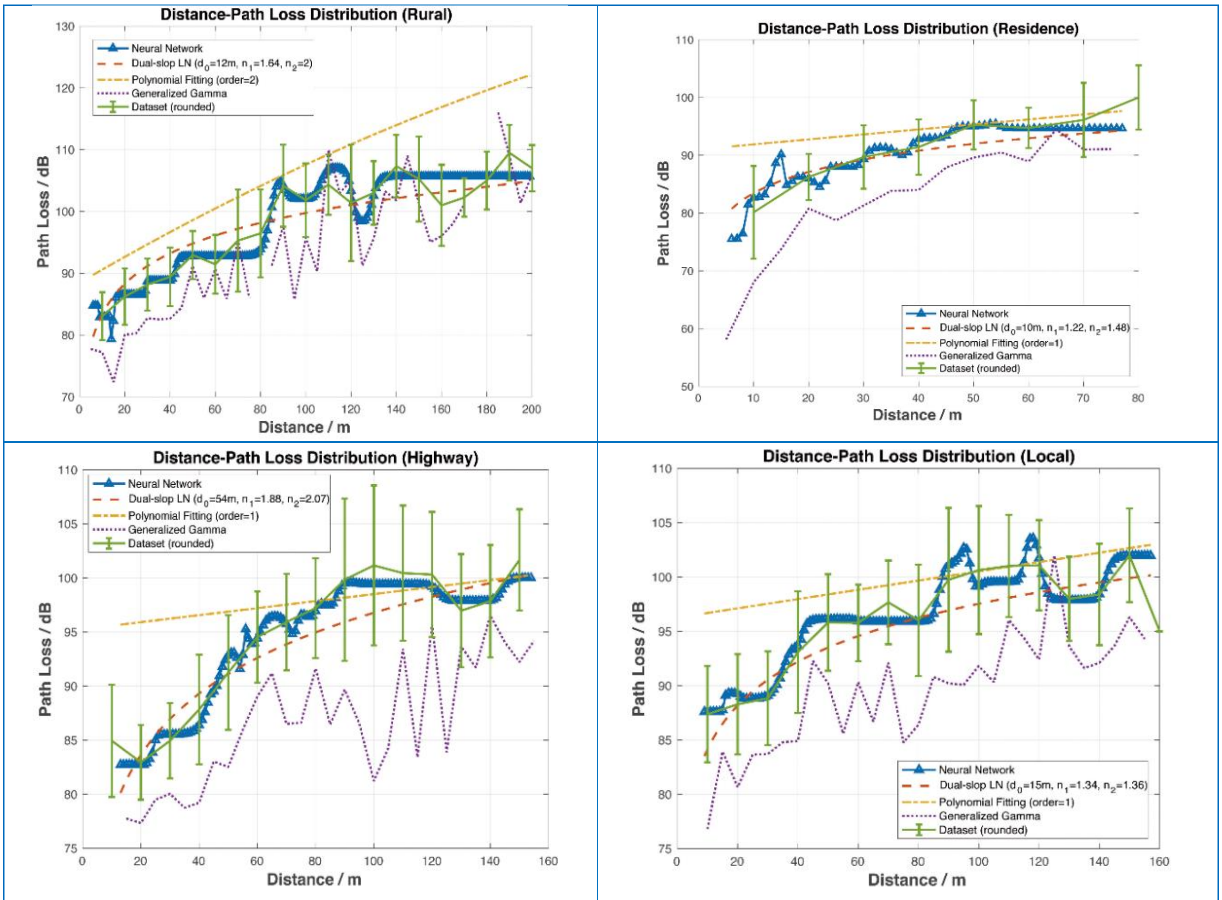


Fig. 11. Comparison of four different path-loss prediction approaches (including NN-based and baseline estimators) as evaluated in [41].

2.2.5 Deep Learning -Based Path Loss Prediction

Following ML models, DL approaches enhance prediction capacity by employing multi-layer neural networks and, increasingly, multi-modal sensing to capture complex propagation factors in urban scenarios. In [42] The authors propose a multi-modal DL framework for PL prediction in urban intersections. The model combines multiple components CNN/UNet for image-like inputs, a Point CNN for point-cloud representations, an attention module (CAM), and an MLP regressor to fuse heterogeneous sensing modalities into a unified PL estimate. Fig. 12 illustrates the overall architecture and the role of each module in the fusion pipeline. The reported results show a very low prediction error (MSE = 1.9283×10^{-6}) and an improvement equivalent to a two-degree gain on the 3GPP TR 38.901 scale. Moreover, the proposed multi-modal model achieves 19.8% higher accuracy than a single-modal baseline and outperforms several conventional ML methods (ANN, SVR, RF, and GTB) under the evaluated settings. The study also notes that the Som-evoke concept can exploit additional environmental cues by retrieving information from dormant device antennas, which may further strengthen contextual awareness for PL prediction.

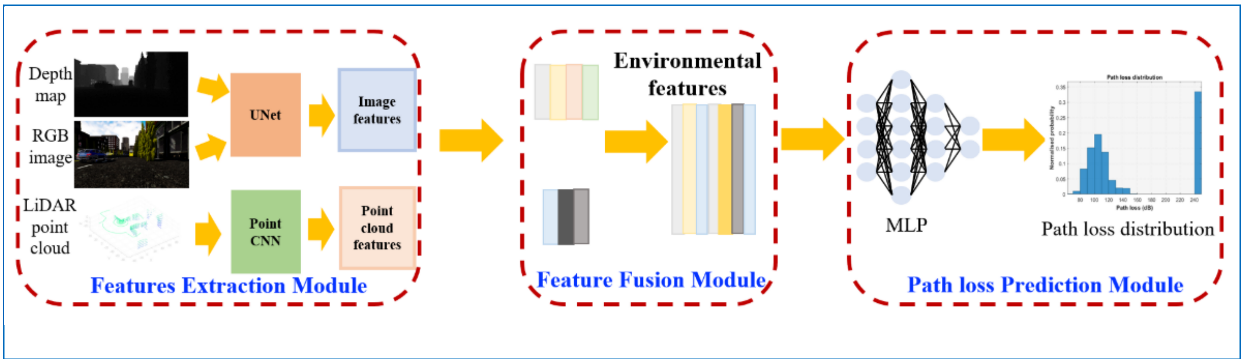
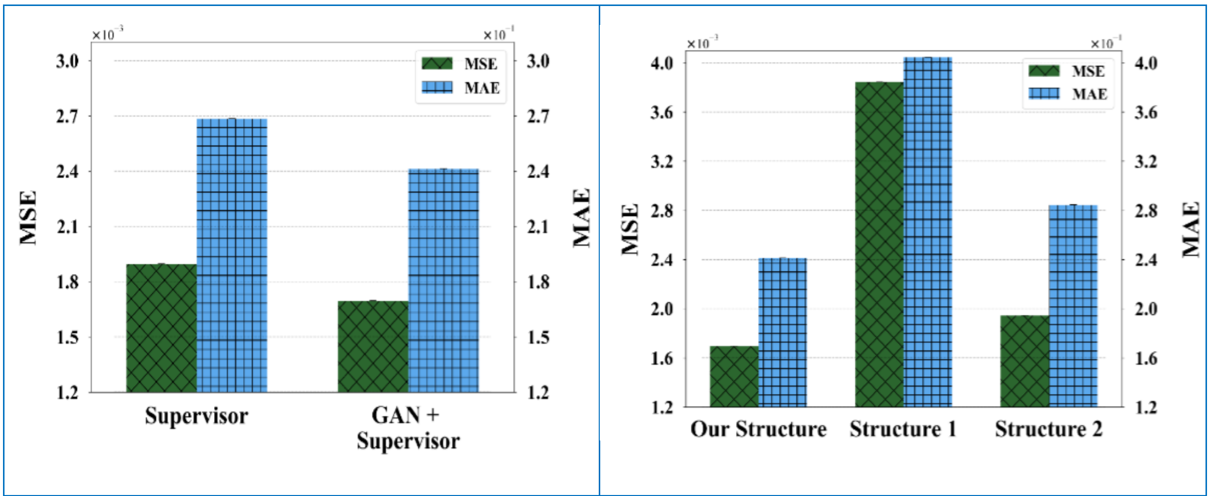


Fig. 12. Structure of the proposed multi-modal DL architecture for path-loss prediction, showing the main modules for feature extraction and fusion (e.g., CNN/UNet, Point CNN, attention, and MLP regressor)[42].

The authors [43] propose an AI-enabled PL prediction framework for V2X communications within the Integrated Sensing and Communications (ISAC) paradigm. The model predicts the end-to-end PL distribution by fusing multi-modal sensing inputs (camera images, LiDAR, and radar). Prediction parameters are initialized and then refined via supervised learning supported by a Generative Adversarial Network (GAN). The reported performance achieves an MSE below $3\times10{-}3$ across five evaluated scenarios. Fig. 13 summarizes the comparisons in [43] Fig. 13(a) examines the impact of different training strategies, while Fig. 13(b) compares the proposed approach against alternative PL prediction methods, showing lower error and more stable performance for the multi-modal ISAC-based model. The authors suggest improving LiDAR processing and extending the framework toward 3D representations. Nevertheless, transferring such a sensing-driven PL predictor to practical V2I deployments requires further validation on real-world vehicular datasets with diverse LOS/NLOS transitions and mobility conditions.



(a) model performance under different training strategies.

(b) Comparison of the proposed method against baseline path-loss prediction approaches.

Fig. 13. Experimental comparisons reported in [43].

In paper [44], the authors detail a path loss prediction model for mmWave vehicular-to-vehicular communication utilising deep learning, as part of existing 5G systems. The authors implement their own standalone simulation framework, constructed using the NS-3 network simulator and SUMO traffic simulator tool, based upon simulated environments including varying channel conditions (e.g., LOS, NLOS, NLOSy) and weather conditions, including sunny, rainy, and snowy. To develop a path-loss prediction model trained for mmWave V2V communications, the authors construct and train a deep neural network (DNN) with 6 layers (i.e., 6 hidden layers) to model the nonlinear relationships between simulation scenario conditions and resulting path loss. The authors note the shortcomings of traditional path-loss prediction models regarding both the constructs used in constructing the prediction models and in the accuracy of evaluating the prediction models in highly dynamic simulation environments. The authors also caution that, as they generate their data by simulation, any performance reported using this approach cannot necessarily be generalised to real-world deployments.

Finally, the authors suggest that the approach can be extended to additional V2X scenarios such as V2I and V2P scenarios. Building on the trend of learning from richer context information, the study in [29] introduces a multi-modal environmental sensing-based route loss prediction architecture (MES-PLA) for V2I communications. The framework relies on a synchronized multi-modal acquisition platform and employs a multi-modal feature extraction and fusion network (MFEF-Net) with an attention mechanism to integrate GPS, RGB images, and point-cloud data. In simulation-based evaluation, MES-PLA achieves an RMSE of 2.20 dB, outperforming a single-modal baseline. Moreover, the multi-modal design demonstrates improved robustness under varying illumination conditions, indicating that sensor fusion can enhance the stability of V2I path loss prediction in challenging environments. Future work aims to increase environmental diversity and extend the framework toward more comprehensive urban path loss prediction.

Overall, these two studies suggest that deep models can benefit from scenario-aware inputs, either through controlled simulation conditions or real multi-modal sensing.

However, rigorous validation on real-world V2I datasets remains a key requirement for deployment. Given the diversity of propagation settings and modeling approaches, a structured summary is necessary. Therefore, Table 4 consolidates the main characteristics of the reviewed studies to enable direct comparison and to highlight emerging trends and remaining research gaps.

Table 4: Consolidated comparison of surveyed V2I/V2X path-loss studies (Section 2.2), summarizing: reference, frequency band, scenario, model/method, key input features, dataset type (measurement/ simulation), reported metrics, and the main takeaway.

Ref.	**Model / Method**	**Frequency**	**Scenario**	**Key Inputs**	**Dataset Type**	**Metrics**	**Main Takeaway (for Section 2.2)**
[32]	Log-distance vs. experimental PL models (T1–T4)	2.4 GHz	V2V + V2I	Distance + scenario conditions	Measurements	MAPE, MSE, RMSE, Ts	The best model depends on the Scenario obstruction degrades V2V more than V2I under the studied settings.
[33]	Log-distance PL model	700 MHz, 5.9 GHz	Urban V2I	Distance, frequency, antenna height	Field measurements	Model parameters (PLE)+trend height	Lower frequency Shows better propagation; the exponent varies with frequency (Figs. 5–6).
[22]	Two-Ray Ground Reflection +Log-distance	5.9 GHz	Urban/ Suburban V2I	Distance, antenna height	Field measurements	PL(d0), γ	Antenna height can reduce the exponent and improve near-range performance.
[34]	3D two-way PE (vs RT)	5.9 GHz	Simplified urban V2I/VANET	Geometry + antenna config	Simulation	Signal level/ coverage	PE and RT give near-consistent results; supports deterministic urban modeling (Fig. 7).
[35]	V2I–VLC PL model (LOS/ NLOS)	Visible light	Mountain-road V2I	Distance + weather	Analysis + simulation	PL, Rx power, capacity, outage	Distance dominates; fog/The weather degrades the link.
[36]	ANN, SVR, RF, GTB (generalization test)	735 MHz,2.54 GHz, 3.5 GHz	V2I (NLOS), “unknown streets” test	Distance + env. profiles	Field measurements	RMSE, MAPE, σ, R²	GTB best; better generalization than log-distance.
[37]	ANN, SVR, RF, GTB vs ABG/CIF (wall-loss extension)	26.5–40 GHz (mm Wave)	Indoor	Distance + wall-related features	Measurements	RMSE / fit-type metrics	ML improves accuracy in high-frequency regimes. trade-off between interpretability and performance.
[38]	XGBoost/ MLP vs Dual-Slope & 3GPP TR 38.901	5.9 GHz	Dense urban V2I	Distance, RSU height, and environmental features	Real measurements	RMSE, R², MSE, MAE	ML strongly improves PL prediction, distance + height + environment are key drivers (Fig. 9).
[39]	MLR, PR, DT, RF, SVR, KNN, ANN,	14, 18, 22 GHz	Indoor corridor (LOS/ NLOS)	Distance, frequency, Tx height AoA	Measurements	RMSE, MAPE, MSE, Corr, R²	Neural models Capture nonlinear propagation with well-chosen features (Fig. 10).

	RNN-LSTM						
[40]	PCA + ANN/MLP + GP	450, 1450, 2300 MHz	Suburban	Frequency, Tx/Rx heights, height ratio, distance	Measurements	RMSE, MAE, MAPE, MSLE, R^2	PCA reduction retains accuracy; ANN-MLP slightly beats GP/linear; two-ray worst due to unrealistic assumptions.
[41]	Real-time ANN/MLP predictor (offline + online)	DSRC 5.9 GHz	Real driving	Distance + speed + GPS/RSSI	Field measurements	RMSE (PL) + PD metrics	NN outperforms empirical baselines and adapts online.
[42]	CNN/UNet + Point CNN + CAM + MLP fusion	28 GHz	Urban intersections	GPS/RGB/point-cloud	Multi-modal dataset	MSE	Multi-modal fusion boosts accuracy vs single-modal & classical ML; architecture in (Fig. 12).
[43]	Multi-modal sensing + GAN refinement	28 GHz, 5.9 GHz	Five scenarios (V2X/ ISAC)	Camera + LiDAR + radar	Dataset from Prior study	MSE	Improves consistency; compares training strategies & baselines; highlights need for real-world V2I validation (Fig. 13).
[44]	6-layer DNN (ReLU, MSE) for PL prediction	60 GHz (mmWave)	V2V (LOS/ NLOS/ NLOSv) + weather	Channel type + weather + scenario inputs	Simulation	RMSE, MAPE, MAE, MaxPE ESD	Promising in simulation; needs real-world validation; extendable to V2I/V2P.
[29]	MES-PLA + MFEF-Net	Not specified	Urban V2I	GPS/RGB/point-cloud	Simulation + sensing dataset	RMSE	Sensor fusion Improves robustness to illumination; needs broader environments + real data validation.

3 Concluding Remarks

This review surveyed PL prediction methods for V2I communications, covering classical empirical models, deterministic approaches, and modern data-driven techniques based on ML, DL, and multi-modal sensing. Across the literature, distance remains the dominant driver of large-scale PL, while antenna height and environment-dependent descriptors consistently improve model fidelity, especially in dense urban conditions. Compared with fixed-form empirical models, ML/DL methods generally provide higher accuracy by learning non-linear interactions, and multi-modal fusion further strengthens robustness when propagation is strongly governed by scene geometry and rapid context changes. At the same time, the evidence highlights recurring gaps: many results rely on simulation-heavy datasets, measurement campaigns are limited in diversity and scale (particularly for mmWave deployments), and the interpretability and reproducibility of complex DL pipelines are often insufficiently addressed. From a practical decision perspective, empirical models remain the preferred choice for early-stage planning, link budgeting, and quick what-if analyses due to their simplicity and interpretability; deterministic methods (RT/PE) are most appropriate when accurate 3D maps are available and site-specific prediction is required; ML models are recommended when moderate-to-large measurement data exist and the goal is strong predictive performance across heterogeneous urban conditions; and multi-modal DL fusion is best suited to challenging NLOS-dominant intersections where scene understanding is critical and synchronized sensors are available. The main limitations of this review are the heterogeneity of reported datasets, feature definitions, and evaluation protocols, which can prevent strict apples-to-apples numerical comparison, and the uneven availability of real-world measurement data across frequencies and environments; therefore, conclusions should be interpreted as evidence-based trends rather than universal rankings. Future work should prioritize open and diverse measurement datasets, standardized evaluation protocols with transparent reporting of inputs and splits, interpretable learning (e.g., SHAP/explainable features), and hybrid approaches that combine physics-based baselines with residual learning to improve generalization and trustworthiness in real V2I deployments.

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