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RESEARCH ARTICLE

Deep Learning-Based Path Loss Prediction for Fifth-Generation New Radio Vehicle Communications

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ABSTRACT Fifth-generation (5G) technology is rapidly spreading to vehicle-to-vehicle (V2V) communication, which requires high reliability, high data transmission rate, and low latency to meet service requirements through a new frequency band called millimeter wave (mmWave). However, mmWave bands are difficult to utilize in a dynamically changing vehicle environment because of the propagation attenuation against obstacles. Various studies are underway to predict the path loss in the mmWave band on roads with many obstacles. However, it is still challenging to accurately predict the path loss in various environments because the existing prediction models either generalize the path loss solely based on measurement data or only use specific parameters. Recently, investigations on artificial intelligence have been conducted using various techniques that are different from the existing heuristic methods. Following this trend, we propose a deep learning-based path loss prediction that considers obstacles on roads and weather conditions in V2V communication using mmWave. To consider the various environments affecting measurement, we constructed a realistic simulation environment and collected data that we used to train our deep learning models. Our proposed deep learning-based approach achieves accurate predictions for path loss.

INDEX TERMS Path loss prediction, vehicle-to-vehicle communication (V2V), millimeter wave (mmWave), deep neural network (DNN), weather condition modeling.

I. INTRODUCTION

Vehicle to everything (V2X) communication can improve road safety, user convenience, and traffic congestion by sharing traffic information between the surrounding environments and vehicles. Traffic and vehicle control information exchanged via V2X communication are essential to planning safe vehicle maneuvers. For a complete autonomous driving service, this information must be reliably transmitted and received with short latency, high communication success rate, and massive data transmission, forming key requirements for V2X communication. To satisfy these service requirements, fifth-generation (5G) communication technology is more suitable for V2X communication than fourth-generation (4G) communication, which focuses on communication for smartphones.

5G uses new radio (NR) technology as a new radio access technology (RAT). In addition, NR can improve terminal miniaturization, inter-terminal communication latency, burst data transmission, and frequency reuse of communication terminals using the millimeter wave (mmWave) band [1], [2]. Although mmWave can achieve a higher bandwidth with lower latency, it has a critical drawback in terms of serious propagation attenuation owing to its short range and signal blockage problems caused by its high-frequency band [3].

In the vehicle communication environment, mmWave signal propagation is aggravated by weather conditions, objects, and the distances between vehicles [4]. In particular, this

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signal degradation of mmWave in V2V communication, which rapidly exchanges data, can lead to poor reception of critical data, potentially causing safety problems, including accidents.

Wireless signal degradation can be represented through a channel model, which is a mathematical representation of the effects of a communication channel. In channel modeling, path loss is a key element that describes how the power density of a radio wave decreases as it propagates through the channel [5]. Major challenges in using mmWave bands for V2V include the accurate prediction of two models, path loss and multipath fading, and explaining propagation characteristics [6].

Traditional research on predicting path loss and multipath fading is approximately twofold: (a) *a deterministic method* that models and predicts the radio propagation environment and (b) *a statistical method* that can be applied for prediction in similar environments by leveraging measurement [7], [8]. Path loss prediction using the *deterministic method* allows accurate prediction in a short range through a detailed description of the principal features for all objects in the environment. However, applying this method for accurate prediction in a long-range setting is difficult because the computational cost significantly increases and relies heavily on detailed and precise descriptions of all objects in the radio wave space.

The *statistical method* of predicting path loss through data measured in a specific radio propagation environment has the advantages of feature parameters obtained from the environment, which are not included in the measured data. However, this method suffers from lower reliability in new environments (e.g., variance in obstruction, building, and vehicles) and has difficulty in accurately predicting path loss because the characteristics of the environment cannot be predicted for new environments. One advantage of the statistical method is that the prediction accuracy can be easily improved by collecting more measured data from various environments. Nevertheless, challenges remain in measuring the path loss during V2V communication in dynamic environments, such as with various channels and weather conditions.

In this context, we propose a *novel path loss prediction method* based on deep learning to address the aforementioned limitations of existing approaches. Our proposed path loss prediction method uses a deep neural network (DNN) algorithm to predict the path loss of 5G V2V communication under various communication channel states in mmWave and weather conditions. The goal of the proposed approach is to predict the path loss by considering both the communication environment and weather conditions.

To collect massive amounts of data, we used a combination of simulators that are well designed and therefore proven to be realistic and accurate [9], [10], [11]. We included the International Telecommunication Union (ITU) recommendations for attenuation prediction that add various weather conditions to our path loss model; this has been proven valid in various studies [4], [12]. It is also possible to conduct a comprehensive simulation study to gain path loss data on mmWave-based V2V communication in almost the same vehicle scenarios as in reality. Our DNN-based path loss prediction approach for mmWave-based V2V is based on a large amount of data obtained, considering realistic road environments, including communication environments and weather conditions. Therefore, we implemented practical V2V communication scenarios by integrating two different types of simulators: a network simulator (ns-3) and a traffic simulator, SUMO. Both ns-3 and simulation of urban mobility (SUMO) are well-known, validated open-source simulators.

Our approach considers three categories of traffic environments to comprehensively cover road conditions: line-of-sight (LOS), non-LOS (NLOS), and NLOS by vehicle (NLOSv). Our approach also considers three types of weather conditions: sunny, rainy, and wet-snowy. Using these conditions, we constructed four representative scenarios for experimenting with V2V environments that are further explained in Section VI.

Our contributions are summarized as follows:

- We significantly improved the accuracy of uncertain feature extraction for a new environment of statistical and deterministic prediction methods using the DNN model.
- We applied a realistic ITU standardized fading prediction model to consider weather conditions (especially for wet snow) on mmWave communication in the 60 GHz frequency band for V2V communication, which has not been explored sufficiently in the literature.
- We considered and tested scenarios in realistic traffic environments: (1) LOS, (2) NLOS, (3) NLOSv, and (4) a combination thereof, which greatly improves the prediction accuracy, particularly in mmWave environments.
- Our proposed approach predicts path loss with high accuracy (0.87[dB] RMSE, 0.56[%] MAPE, 0.66[dB] MAE, 3.76[dB] MaxPE, and 0.87[dB] ESD).

The rest of the paper is organized as follows: section II presents a survey of the background of relevant technologies, and Section III presents a literature review of the existing related studies. In Section IV, we propose a novel path loss prediction approach using deep neural networks with the design and implementation of the approach. Section V describes detailed simulation modeling methods for obtaining training data. Section VI presents a performance evaluation of the proposed approach, followed by a discussion. Finally, Section VII concludes and discusses future work.

II. BACKGROUND

A. 5G NEW RADIO FREQUENCY: FREQUENCY RANGE 2 – MILLIMETER WAVE

Intelligent transport systems (ITS) application utilized communications below 6 GHz; however, different frequency bands could be possible candidates in the future. In particular, V2V requires the support of communication schemes above 24 GHz, called mmWave, because of its data integrity and broad bandwidth [13].

The mmWave band enables higher data rates and supports more applications and use cases than previous frequency bands while providing reliability and ultralow latency. However, realistic issues with mmWave such as path loss and propagation limits have limited its use in V2V services. When bad weather conditions or disturbances occur, these issues substantially restrict the availability of V2V communications. Therefore, they also have an impact on range limitations and communication stability.

A recent study focused on radio characteristic analysis following the introduction of a new frequency band mmWave in V2V communication: path loss, shadow processing, and multipath fading. These radio characteristics of mmWave were analyzed in terms of channel conditions and the environment. This is because the communication performance between transceivers in a dynamically changing road environment is significantly affected by obstacles to the communication channel condition.

The frequency bands of 5G are discussed in Release 15-16 of the 3GPP, leading the 5G standard to be divided into frequency range 1 (FR1) and frequency range 2 (FR2) as follows:

1) **Frequency range 1 (FR1)** contains sub-6 GHz frequency bands, some of which have been expanded to accommodate prospective additional spectrum offers from 410 MHz to 7125 MHz.
2) **Frequency range 2 (FR2)** covers frequency ranges between 24.25 and 52.6 GHz This millimeter-wave range has a shorter range but more available bandwidth than the FR1. Currently, the use of the frequency band above 52.6 GHz of the existing FR2 band is also being discussed in Release 17.

B. PATH LOSS PREDICTION AT THE mmWave BAND

Path loss is a decrease in the power density of the receiving side caused by a range of factor, such as free-space loss, diffraction, reflection, refraction, absorption, terrain contour, and distance [14]. When designing a wireless network using path loss prediction, it can be used to determine the effective service area of a base station and define a propagation shadowing region based on the position of the base station. Furthermore, a transmitter can be designed by considering the transmission power, reception sensitivity, and antenna height [15].

Path loss in the mmWave band is more susceptible to external effects than in other frequency bands because of the high-frequency characteristics of mmWave and various physical phenomena unique to mmWave, such as obstacles, atmospheric attenuation, and rainfall attenuation [14].

Consequently, conventional path loss prediction approaches may result in lower prediction accuracy at mmWave.

C. CHALLENGES IN DEEP LEARNING-BASED PREDICTION

In recent years, prediction methods using deep learning have shown superior performance compared to conventional prediction methods. Theoretically, the deeper the network, the higher is the dimension of the characteristics from the input, and thus, the accuracy of the prediction can be improved [16], [17]. However, more layers can harm performance. As the number of layers increases, two major problems arise.

Overfitting can be caused by the large number of neurons in the hidden layer. For example, overfitting occurs when a neural network has excessive information processing capability and the training set has insufficient information to train all the neurons in the hidden layer. Furthermore, an excessive number of neurons in the hidden layer may significantly increase the network training time, making neural network training impractical [17], [18].

Underfitting occurs when too few neurons are used in hidden layers, that is, the hidden layer has insufficient neurons to detect a complex dataset [18].

Therefore, a compromise must be made between too many and too few neurons in the hidden layers. Methods for determining the optimal number of hidden layer neurons were introduced in [19].

III. RELATED WORK

This section discusses existing related studies for applying a novel path loss prediction approach. This section includes studies of V2V communication using mmWave, simulation-based analysis studies of existing mmWave V2V communication for V2V communication, existing path Loss prediction methods, and artificial intelligence-based path Loss prediction studies.

A. mmWave IN V2V COMMUNICATION

Various studies have been conducted to improve reliability and achieve low latency for V2V communication [28], [29], [30]. Most of their eventual goals were mainly to enhance the V2V communication performance for improved traffic safety and driving convenience. The key enabler of V2V is the use of mmWave waves, which can solve the problems of high communication speed and capacity in V2V communication by providing a wide bandwidth in the high-frequency band.

The mmWave band enables higher data rates and supports more applications and use cases than previous frequency bands while providing reliability and ultralow latency. However, realistic issues with mmWave, such as path loss and propagation limits, have limited its use in V2V services. When bad weather conditions or disturbances occur, these issues substantially restrict the availability of V2V communications. Therefore, they also have an impact on the range limitations and communication stability.

A recent study focused on radio characteristic analysis following the introduction of a new frequency band for

TABLE 1. Comparison of previous mmWave V2V communication studies (used similar form in [20]).

Reference	Channel condition	Environment	Frequency band	Mobility	Analysis method	Weather
[4]	LOS, NLOS, NLOSv	Urban, highway	Wide band; 60 GHz	Dynamic	Statistical method	Sunny, Rain, Rain and Wet Snow
[21]	LOS, NLOS	Open area	Narrow band; 60 GHz	Static	Statistical method	-
[22]	LOS, NLOS	Urban, highway	Wide band; 30, 60, and 73 GHz	Static	Statistical method	-
[23]	LOS	Highway, regular city road	Narrow band; 60 GHz	Dynamic	Statistical method	-
[24]	LOS	Airport taxiway	Narrow band; 60 and 63 GHz	Static	-	-
[25]	LOS, NLOS	Regular city road	Narrow band; 77 GHz	Static	Deterministic method	-
[26]	LOS	Urban	Wide band; 73 GHz GHz	Dynamic	Statistical method	-
[27]	LOS	Urban street	Wide band; 60 GHz	Dynamic	Statistical method	-
Proposed approach	***LOS, NLOS, NLOSv***	***Urban, highway***	***Wide band; 60 GHz***	***Dynamic***	***DNN-based method***	***Sunny, Rain, Rain and Wet Snow***

mmWave in V2V communication [6], [13], [21], [31]: path loss, shadow processing, and multipath fading. These radio characteristics were analyzed in terms of channel conditions and the environment. This is because the communication performance between transceivers in a dynamically changing road environment is significantly affected by obstacles to the communication channel condition.

B. TRADITIONAL SIMULATION-BASED APPROACHES for mmWave V2V COMMUNICATION ANALYSIS

Research on channel analysis in the mmWave band has been actively conducted to analyze the characteristics of high-frequency bands. Yamamoto et al. [21] studied path loss prediction for V2V communication in the 60 GHz band; however, their analysis was based on static scenarios.

Bobbin et al. [22] studied V2V channel characteristics by considering multiband blockages. TABLE 1 summarizes a variety of previous channel studies on mmWave bands for V2V communication.

As stated in [32], on the other hand, simulation is an important factor in modern research to gain insight into the operation of complex systems. In addition, the characteristics of the simulation, which can be adjusted in detail, are the advantages of allowing the causal relationship between design and performance to be determined. Furthermore, most current studies on channel and propagation characteristics use a simulation-based approach because path loss experiments in real-world environments are limited by cost, time, and safety issues [33], [34], [35]. Whether the simulation is designed to reflect realistic elements is a key element for performance results. Case of the path loss analysis in V2V communications is also a complex system and is affected by a variety of factors.

Previously, there have been various studies analyzing path loss based on simulations [4], [20], [32], [36], [37], [38]. Several mmWave channel model simulators, such as NYUSIM [39], [40], focus on 5G mmWave developed using statistical methods based on representative path loss models.

However, these mmWave channel model simulators were designed for cellular networks that neither consider traffic nor describe vehicle communication accordingly. In a V2V communication environment, the dynamic location characteristics of the vehicle transceiver results in rapid changes in the communication channel. Therefore, the analysis of the V2V communication channel should reflect rapid changes in the communication and transportation environment.

Furthermore, since path loss model using in conventional ns-3 are based on simple statistical models, they exhibit low performance in complex real-world environments. For this reason, realistic evaluation requires an attempt to implement realistic models such as vehicle channel models on the network simulator [41].

Simulation testbeds through the integration of Network Simulator 3 (ns-3) and SUMO can be a reliable alternative as a tool to analyze V2X communication in the mmWave frequency band. Dice et al. [4] and Zuni et al. [42] recently developed a simulated ns-3 module that includes a channel model for V2V communication in the mmWave frequency band that complies with 3GPP channel requirements. The simulator can also configure communication channels for V2V communication applications by applying ITU weather model.

In [4], V2V communication was implemented using an ns-3 MilliCar module for mmWave NR V2X communication. Traffic was implemented using SUMO. Through the integrated simulator, it is possible to realistically and efficiently perform V2V communication simulations.

C. TRADITIONAL PATH LOSS PREDICTION METHODS

Traditional path loss prediction methods have two representative categories: deterministic and statistical methods [43]. Deterministic models can make accurate predictions but require highly accurate topographic data and are numeric processing-intensive. They also depend on the geometric information, computational effort, and accuracy of a site.

Deterministic methods are based on the physical laws of wave propagation such as ray tracing. These approaches are supposed to provide more accurate and reliable predictions of path loss than statistical methods [7], [8].

Statistical approaches, however, are based on measurements and statistical properties [44]. This model is a simple approach for determining path loss without considering all the factors that can influence it.

One of the important components in the statistical model is distance information, which can be formally represented by a linear logarithmic distance function. Most traditional statistical models use linear logarithmic distance path loss and shadow models as criteria, as provided in [45] and [46]. In addition, statistical models analyze the effects of parameters such as the frequency of communication, the height of antennas, noise and terrain, LOS, and NLOS [47], [48], [49], [50], [51].

Recently, Jo and Yolk [52] improved the modified Hata model as a statistical model by measuring in a high-frequency band environment of 3–6 GHz.

1) DETERMINISTIC METHOD

Models that employ fundamental physical principles and are based on available theorems and theoretical explanations. To construct a model or approach, these methods consider all the physical factors inside a particular region, and the outcomes are better and more accurate. However, the main disadvantage of these approaches is that they can only be utilized for short-range communication when the quantity of necessary data is contained within a small region. Existing equations derived from the outcomes of many measurement attempts are used in deterministic models.

2) STATISTICAL METHOD

For various types of environments and radio networks, this approach predicts path loss using practically measured values of loss and averaging loss. Different situations necessitate different approaches such as Okumura-Hata, COST231-Hata, and ECC-33 [47], [48]. These models have characteristics that are mostly dependent on the environment at the time of measurement.

- Okumura-Hata model: The Hata model is a propagation model that can be used to predict the path loss of cellular communication in outdoor conditions. This is valid for microwave frequencies between 150 and 1500 MHz.
- COST Hata: The COST Hata model is a radio propagation (i.e., path loss) model that extends the urban Hata model (which is based on the Okumura model) over a frequency range (up to 2 GHz).
- ECC33 Hata: The ECC33 model, based on the Okumura model, is frequently used in urban areas.

D. ARTIFICIAL INTELLIGENCE-BASED PATH LOSS PREDICTION

Machine learning – a data analysis method that automates analytical model building – is a rapidly growing technology in data science. A statistical approach to machine learning can be used to learn classification or prediction algorithms. Machine learning technology has recently been employed in various research areas, including self-driving and signal processing, for accurate prediction [44], [53].

In recent research, machine learning for path loss prediction has been shown to be more accurate than traditional prediction models [54], and a machine learning-based prediction model can minimize the analysis time for propagation scenarios.

Regression has been used to predict propagation path loss. In this setup, supervised learning approaches such as support vector machines, artificial neural networks (ANNs), random forests, and KNNs, have all been attempted in path loss models. The authors have used ANN models to predict path loss and showed that ANN models are more accurate than traditional statistical approaches [44], [55], [56].

IV. PROPOSED APPROACH

In this section, we propose a novel deep-learning-based path loss prediction system using a DNN model that improves learning outcomes by increasing the number of hidden layers in the ANN. We used a multiple linear regression framework for predicting path loss, considering independent variables such as precipitation, channel status, and road traffic. Our DNN-based prediction approach consisted of two phases: training and testing. The overall structure of the proposed path loss prediction system is shown in FIGURE 1.

This section describes our proposed simulation-based path loss prediction system structure, simulation environment, training of deep learning, test data, training of deep neural networks for path loss prediction, descriptions of test procedures, and DNN training algorithms.

A. PROPOSED SIMULATION-BASED PATH LOSS PREDICTION SYSTEM STRUCTURE

Our proposed system is largely divided into three parts: a vehicle communication simulation environment part built to acquire path loss data, a learning part of a deep learning model, and an experimental part of learned deep learning.

We constructed a simulation environment by combining traffic simulators and network simulators. To analyze weather conditions and multipath effects in a vehicle communication environment, we used a path loss model based on weather conditions by ITU-R and a path loss model based on vehicle communication channel conditions by 3GPP (e.g. LOS, NLOS, NLOSv). Also, we considered two propagation environments: urban and highway roads.

To obtain sufficient and diverse data for training the DNN model, we collected training data from the simulator while changing the communication and traffic environment of the road. The specific training data collection environment is shown in Figure 1 in the simulation environment.

To establish a model for training to find a solution for problems, the neural network model used in the training phase was designed in six layers using the ReLU activation function and the mean squared error (MSE) loss function to calculate the difference between actual and predicted data.

In the test phase, we obtained the test data from the simulation environment. The test data was not used during the training phase and consists of data excluding path loss from the training data. The output data were path loss values predicted by different environmental parameters.

B. SIMULATION ENVIRONMENT

In the simulation environment, our purpose was to collect training data for the DNN in various situations using a simulation testbed.

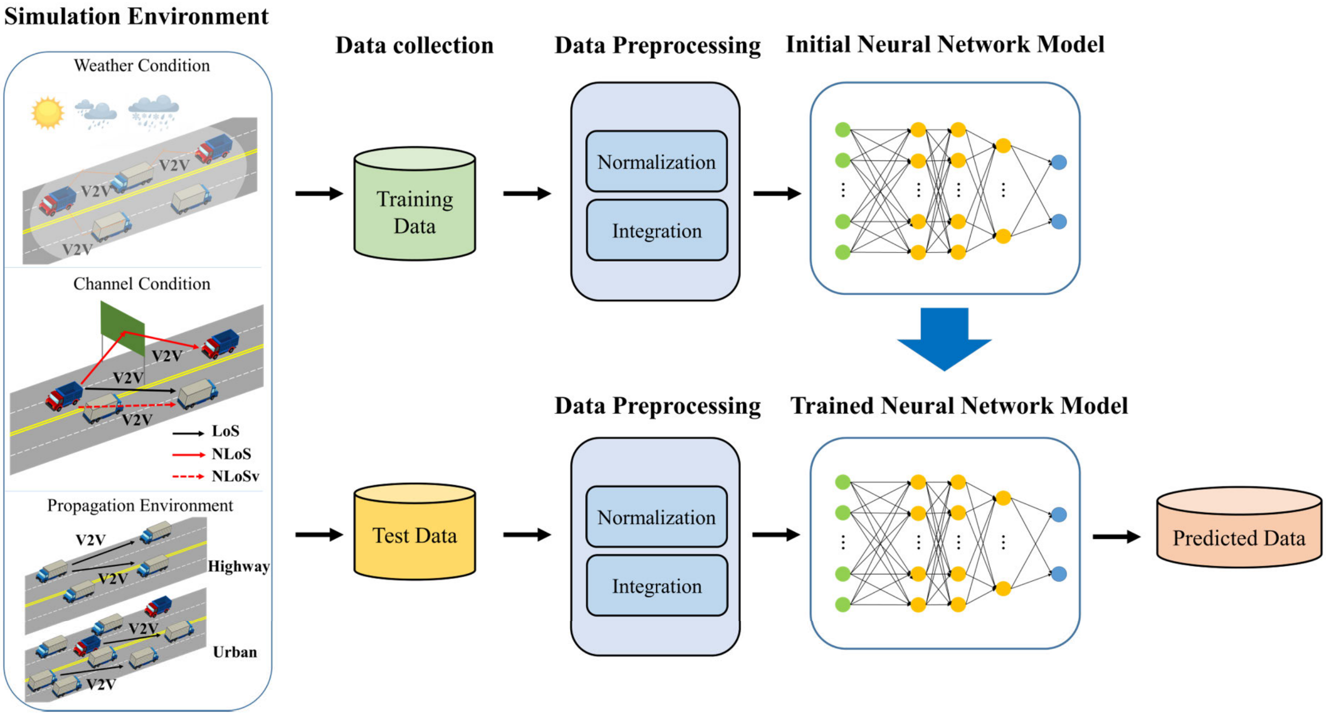


FIGURE 1. Overall architecture of proposed path loss prediction system.

Because changing the experimental environment in actual weather conditions is limited, we used a simulation environment combined with a network simulator and traffic simulator. The network simulator allowed the modeling of radio channels and created a network topology, and the traffic simulator enabled the control of vehicle traffic. A dynamic V2V communication environment was implemented by combining these two simulators. We obtained experimental data using the combined simulation testbed.

We applied two main parameters that affect the path loss in vehicle communication: multipath fading and weather conditions. Multipath fading in urban and highway scenarios applies the following three main types of V2V communication conditions:

- LOS signals are propagated through a direct path, as the communication path between the transmitter and receiver vehicles is clear.
- NLOS signals are propagated through an indirect path, as the communication path is blocked by static blockages.
- NLOSv signals are propagated through an indirect path, as the communication path is blocked by dynamic blockages.

We applied following three weather conditions:

- Sunny weather: the attenuation values for the coefficients set at a raindrop rate of 0 mm/h are presented.
- Rainy weather: specific rain attenuation values for the coefficients determined as functions of frequency and various raindrop rates are presented by ITU-R for use in prediction methods.
- Wet snowy: the attenuation values from combined rain and snow are presented.

TABLE 2. Experimental data configuration.

Data type	Parameters	Value
Constant data	Frequency	60 GHz
	Bandwidth	250 MHz
	Data rate	300 Mbps
	Antenna height	20 m
	Number of antenna element	20
	Vehicle speed	20 m/s
	MCS	20
Variable data	Scenarios	Urban, highway
	Intensity of rain	2.5, 20, 30, 40 mm/h
	Weather	Sunny, rainy, wet snowy
	Channel condition	LOS, NLOS, NLOSv

C. TRAINING & TEST DATA

We preprocessed the collected data using one-hot encoding and batch normalization to train the deep neural network model. The configuration of each input data has common parameters such as frequency band of 60 GHz, antenna height of 20 m, and bandwidth of 250 MHz. The parameters used for training deep learning model are set as listed in TABLE 2.

D. DEEP NEURAL NETWORK FOR PATH LOSS PREDICTION

We used a six-layer DNN model for path loss prediction. To construct the DNN prediction model, we included the

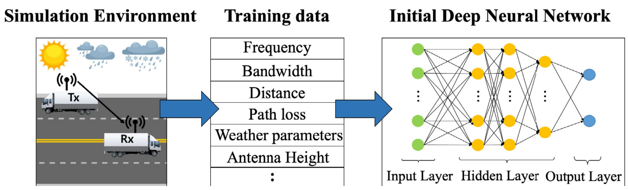


FIGURE 2. Training Phase of proposed prediction system.

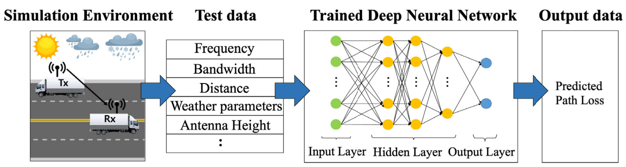


FIGURE 3. Testing phase of proposed prediction system.

activation function of ReLU, and the loss function of MSE. The DNN prediction model is divided into a training phase and a test phase. FIGURE 2 describes the three-steps in the training phase and FIGURE 3 shows the four-steps in the testing phase.

1) TRAINING PHASE

Dataset obtained through the simulation was used for learning the DNN model. The dataset including path loss data was used as the training data. Especially path loss data is label data. At this time, 30% of the training data were used to verify the validity. All data were classified into numerical data and categorical data, and the scales of the distributed values were different. Therefore, before starting training, the efficiency of learning was improved through normalization. FIGURE 2 illustrates the training phase for the proposed path loss prediction system.

2) TEST PHASE

To confirm the objective predictive accuracy performance of the learned DNN model, a new dataset that was not used in the training stage was used in the test phase. To collect a new dataset, simulation data were collected by introducing different experimental conditions such as weather conditions that had not been used in the training phase. After predicting the rest of the data, except for the path loss of the new dataset, we verified the prediction accuracy by comparing it with the actual path loss value. The accuracy of the path loss prediction of the model was evaluated during the test phase, as shown in FIGURE 3.

As with most deep learning algorithms, our proposed method is divided into training and testing steps. Both the training and test data were generated using environmental simulators and vehicle-to-vehicle communication scenarios.

The deep learning network model learning process involves preprocessing to separate the labels of the training and test data. Labels for training data use path loss data and the remaining fields in the dataset become the fields for training. The test data included the remaining fields, except the path loss field, and used the path loss data to verify the prediction results. Preprocessed data were used for learning and testing through normalization and one-hot encoding.

Algorithm 1 Deep Neural Network Training Procedure

Data preprocessing:
Divide the dataset into a training set and a test set
$label_{train}$, $data_{train}$: path loss(label) and others
$test_x$, $test_y$: path loss(label) and others
Dataset normalization & one hot encoding

procedure BUILDMODEL() Add hidden layers with a number of nodes (units) and an activation function (ReLU).
layer.Dense(units=32, activation=ReLU)
layer.Dense(units=48, activation=ReLU)
layer.Dense(units=32, activation=ReLU)
layer.Dense(units=16, activation=ReLU)
layer.Dense(units=12, activation=ReLU)
layer.Dense(units=4, activation=ReLU)
Add an output layer.
layer.Dense(1)
end procedure

procedure TRAINING($data_{train}$, $label_{train}$)
while not convergence **do**
$model(data_{train}, label_{train} epochs, valid_{split})$
Calculate Loss Function(MSE) $\frac{1}{N}\Sigma(\mathbf{y_i}-\hat{\mathbf{y}}_\mathbf{i})^2$
Back propagation
end while
end procedure

Output:
w_{ij}^l, b_j^l: Weight and bias of neural network
* Required function: Earlystopping, Dropout

As shown in Algorithm 1, six hidden layers were added during the construction of the deep learning model. The activation function of each hidden layer used ReLU, and the number of nodes was determined using the empirical method [26]. The output layer used a single layer to verify the path loss data.

In the learning process, the label fields of the training data and the remaining fields were used, and the learning process proceeded for a given epoch. In addition, the learning process included the optimization of the loss function with training and validation datasets on prebuilt models. Once the learning was complete with a given epoch, the deep learning model had optimal weights and biases, which were saved in the form of a model file for use in testing.

V. SIMULATION MODELING

This section details the investigation of the experiment environment setup, vehicle communication model used in the experiment, and weather model. The vehicle communication environment consisted of a combination of validated simulators to construct a realistic experiment environment. In the experiment environment, we considered both the V2V channel status and vehicle traffic to represent the diversity and reality of the simulation. The channel states considered LOS without propagation obstacles, NLOS with static propagation obstacles, NLOSv with dynamic propagation obstacles, and all these situations together. In addition, we considered two traffic scenarios: urban, where vehicles are mixed significantly, and highway, where there are few vehicles.

A. VEHICLE COMMUNICATION MODELING

When sending a V2V message from one vehicle to another in a vehicle communication environment, the requirements of the radio attenuation analysis are the model of vehicle and radio wave obstruction elements. Through the experimental environment, including the two models, we trained deep learning prediction models and collected the data used for predictions. The vehicle communication simulation environment used a simulator linked to the ns-3 and SUMO.

The ns-3 uses the V2X model in the mmWave band to implement a V2V communication environment. In addition, we secured the reality of the messages exchanged using the standard communication protocol stack of 5G NR V2X. Through SUMO, we designed a vehicle driving environment for downtown areas with many vehicles, and highways with few vehicles, and created traffic conditions on the road, such as vehicle direction and driving speed.

Packets were generated for actual V2V communication, and periodic transmission and reception were modeled. In particular, in a communication environment where packets are transmitted and received, radio attenuation was modeled according to channel environments such as LOS, NLOS, and driving environments. The radio attenuation model was also used in urban areas and highways to evaluate the communication performance of the driving environment built through a simulator. We introduced the 3GPP path loss model[1] to the simulator according to TR 38.886. In a highway environment, the path loss according to the LOS, NLOS, and NLOSv channel states are $PL_{l,h}$, $PL_{n,h}$ and $PL_{v,h}$, respectively, and were calculated using equation (1)–(3).

$$PL_{l,h} = 32.4 + 20log(D) + 20log(F) \tag{1}$$
$$PL_{n,h} = 36.85 + 30log(D) + 18.9log(F) \tag{2}$$
$$PL_{v,h} = 32.4 + 20log(D) + 20log(F) + L \tag{3}$$

In addition, path loss in an urban environment was calculated using the following equations (4)–(6).

$$PL_{l,u} = 38.77 + 16.7log(D) + 18.2log(F) \tag{4}$$
$$PL_{n,u} = 36.85 + 30log(D) + 18.9log(F) \tag{5}$$
$$PL_{v,u} = 38.77 + 16.7log(D) + 18.2log(F) + L \tag{6}$$

[1]We use path loss model equations for NR Uu UE to NR V2X UE of Table 5.2.3-1 in 3GPP TR 38.886.

where the additional loss[2] L is defined as the larger value between 0 and the log-normal random variable, and is given by the following equation:

$$L = \begin{cases} 0, & min(h_t, h_r) > h_b \\ \exp(\mu + \sigma Z), & else \end{cases} \tag{7}$$

where h_t and h_r are the transmitter and receiver heights, respectively. Z is the standard normal variable and μ and σ are given by the following equations:

$$\mu = log(\mu'^2/\sqrt{(\sigma'^2 + \mu'^2)}) \tag{8}$$
$$\sigma = (\sqrt{(log(\sigma'^2/\mu'^2) + 1)}) \tag{9}$$

where μ' and σ' are calculated by the following equations:

$$\begin{cases} \mu' = 9 + max(0, 15log(D) - 41), \sigma' = 4.5, \\ \quad max(h_t, h_r) < h_b \\ \mu' = 5 + max(0, 15log(D) - 41), \sigma' = 4, \\ \quad else \end{cases} \tag{10}$$

B. WEATHER CONDITION MODELING

Compared to other frequency bands, the mmWave band uses high-frequency bands that can be easily affected by various weather conditions when signals are propagated from the transmitter to the receiver [4]. We applied the weather model to reflect weather effects in our experiment, using mmWave to analyze the path loss of 5G NR V2V and collect more diverse path loss data from collection environments that included the vehicle communication model.

The attenuation of radio propagation by weather can be modeled using the fading prediction method described in ITU-R. The weather model includes rain, snow, wet snow that combines rain and snow models, and a sunny weather model, assuming that the weather model was not applied. We used sunny, rain, and wet snow to combine the rain and snow models among the ITU weather models.

1) ITU-R RAIN MODEL

We adopted the ITU-R rainfall model[3] to reflect the weather conditions on the road. The ITU-R rainfall model uses the step-by-step statistical approach described in ITU-RP.530-15 [57] with regression coefficients specified in ITU-R P.838-3 [4], [58]. The parameters used in this attenuation model were the rainfall intensity R (mm/h) obtained from local long-term measurements [59], and the coefficients k and α determined as a function of frequency [58]. In the experimental environment, the rainfall intensity had an integration time of 1 min, with a percentage probability exceeding 0.01%. The attenuation value γ_R can be obtained as follows:

$$\gamma_R = kR^{\alpha} \tag{11}$$

[2]We use additional vehicle blockage loss of NLOSv channel state in 3GPP TR 37.885.

[3]We use Long-term statistics of rain attenuation calculation steps of Attenuation due to hydrometeors in ITU-R P.530-15.

where k and α are vertical and horizontal polarizations, respectively, as in ITU-R P.838-3 [58]. The effective distance is calculated as a product of the communication distance and a distance factor r as

$$r = \frac{1}{0.477d^{0.633}R_{0.01}^{0.073\alpha}f^{0.123} - 10.579(1 - exp(-0.024d))} \tag{12}$$

where d is the communication distance, f is the communication frequency, and α is the exponent of specific attenuation. Finally, the rain attenuation A_r is computed as follows:

$$A_r = \gamma_R d_{eff} = \gamma_R dr \tag{13}$$

2) ITU-R RAIN AND WET SNOW MODEL

We applied not only rain but also the wet snow model that considered rain and snow together, to vehicle communication experiments.[4] It is difficult to implement an accurate wet snow model because it is difficult to collect experimental data on rainfall and wet snow. One reliable prediction method is the integrated attenuation estimation of rain and wet snow [57]. The attenuation of wet snow can be estimated using the combination method of rain and wet snow described in ITU-R P.530-15 [57]. The median rainfall height above the average sea-level h_{rainm} was determined using the formula given in [57]. The *0* isothermal height above the average sea level depends on the geographical location and can be obtained using the digital map provided by ITU-R P.839 [59].

Rainfall height was calculated at the center of the communication link using a height higher than the average sea level of the transmitter and receiver as inputs. Here, h_1 and h_2 are the heights of the link terminals higher than the average sea level, and D is the length (km) of the communication link

$$h_{link} = 0.5(h_1 + h_2) - (D^2/17) \tag{14}$$

The communication link is confirmed to be affected by the melting layer through the following formula

$$h_{link} \leq h_{rainm} - 3600 \tag{15}$$

If h_{link} is lower than $h_{rainm} - -3600$ or equal to it, then the link will not be affected by the melting-layer conditions, and A_p can be taken as the attenuation exceeding $p\%$ of the time, and the method can be stopped. Otherwise, the method continues using the following methods. First, the multiplying factor F is initialized with 0. Second, to model the rain height variability, the method uses 0–48 steps of 100 m relative to h_{rainm}, each with a probability associated according to ITU-R P.530-15 [57]. For each step represented by index i, an addition to the multiplying factor is computed using the following formula:

$$h_{rain} = h_{rainm} - 2400 + 100i \tag{16}$$

[4]We use combined method for rain and wet snow of Attenuation due to hydrometeors in ITU-R P.530-15.

The link height relative to the rain height is calculated as:

$$\Delta h = h_{link} - h_{rain} \tag{17}$$

The addition, the multiplying factor for this value of index i is calculated using:

$$\Delta F = \Gamma(\Delta h)P_i \tag{18}$$

where $\Gamma(\Delta h)$ is a multiplying factor that accounts for the differing specific attenuations according to the height relative to the rain height.

$$\Gamma(\Delta h) = \begin{cases} 0, \quad 0 < \Delta h \\ \dfrac{4(1 - e^{\frac{\Delta h}{70}})^2}{1 + (1 - e^{-(\frac{\Delta h}{600})^2})^2(4(1 - e^{(\frac{\Delta h}{70})^2}) - 1)}, \\ \quad -1200 \leq \Delta h \leq 0 \\ 1, \quad \Delta h < -1200 \end{cases} \tag{19}$$

where P_i is the probability that the link will be at Δh, taken in ITU-R P.530-15 [57]. ΔF was added to the current value of F.

Finally, the attenuation from combined rain and wet snow is estimated as

$$A_{rs} = A_p F \tag{20}$$

where A_p represents the attenuation exceeded for the time percentage p from rain, estimated using the ITU fading prediction model. According to [57], the combined rain and wet snow attenuation A_{rs} can be larger or smaller than the attenuation from pure rain, A_p. In channel modeling, we integrated the ITU weather fading prediction model with the existing channel model to analyze the effects of pure rain and wet snow on 60 GHz radio links.

VI. PERFORMANCE EVALUATION

A. TEST SCENARIOS

We used four representative simulation scenarios based on (a) road environments (highway or urban) and (b) vehicles' driving directions (driving in the same-lane or opposite direction). FIGURE 4 illustrates these four scenarios:

1) Highway–Same lane/direction
2) Highway–Opposite direction
3) Urban–Same lane/direction
4) Urban–Opposite direction

As described in Section V, we modeled the channel and weather environment and tested the proposed DNN-based path loss prediction model using these situations. We intensively analyzed path loss predictions according to communication channels, driving environments, and weather conditions by setting fixed data such as speed, communication speed, frequency band, and bandwidth, in dynamically changing vehicle driving environments.

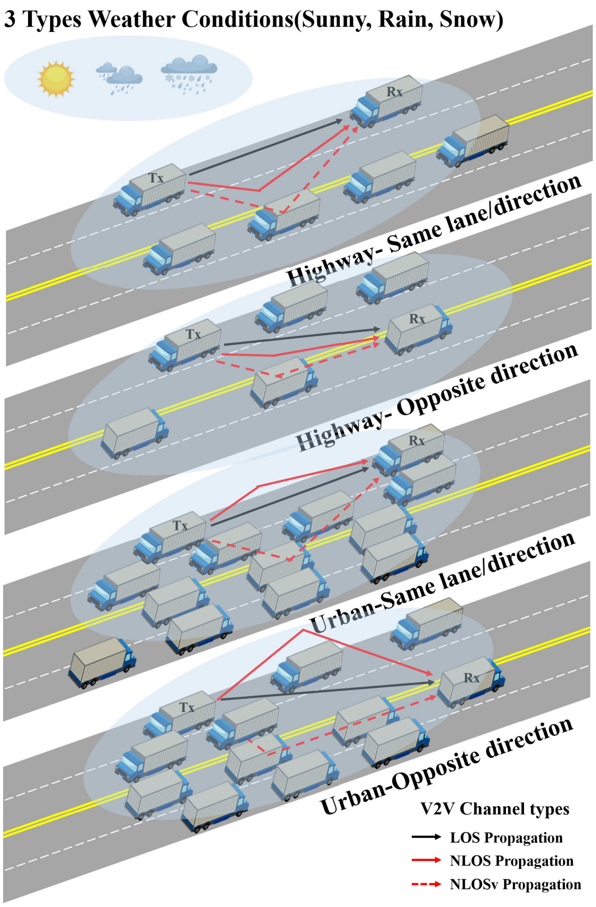


FIGURE 4. Simulation Scenarios for path loss prediction.

B. EVALUATION METRICS

We evaluated the path loss prediction accuracy of the proposed DNN prediction model in the V2V communication environment of driving vehicles. We used five metrics to measure the accuracy of prediction from various angles: root-mean-square error (RMSE), mean absolute percentage error (MAPE), maximum percentage error (MaxPE), mean absolute error (MAE), and error standard deviation (ESD). Using these metrics, we evaluated the performance of the proposed deep learning-based path loss prediction method, where PL_i is the predicted path loss vector, and PL_i' is the actual path loss vector. The description and formula of each metric are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(PL_i - PL_i')^2} \tag{21}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}|\frac{PL_i - PL_i'}{PL_i}| \tag{22}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|PL_i - PL_i'| \tag{23}$$

$$MaxPE = max(PL_i - PL_i') \tag{24}$$

$$ESD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(PL_i - PL_i')^2} \tag{25}$$

C. RESULTS AND DISCUSSION

We compared the prediction performance of the DNN models learned by channel, road situation, and weather characteristics to consider the characteristics of the dataset when learning from the proposed prediction model. In particular, we considered two scenarios: a driving scenario that intersects each other in the opposite direction, and a driving scenario that gradually moves away in the same direction.

We classified the total data into three categories – weather, scenario, and channel – to evaluate the difference in the model's prediction accuracy for each given situation in the experiment. Specifically, we divided the datasets into rain, snow, highways, cities, LOS, NLOS, and NLOSv. The predictive accuracy of the deep learning models learned from the total data, without classification, were also compared.

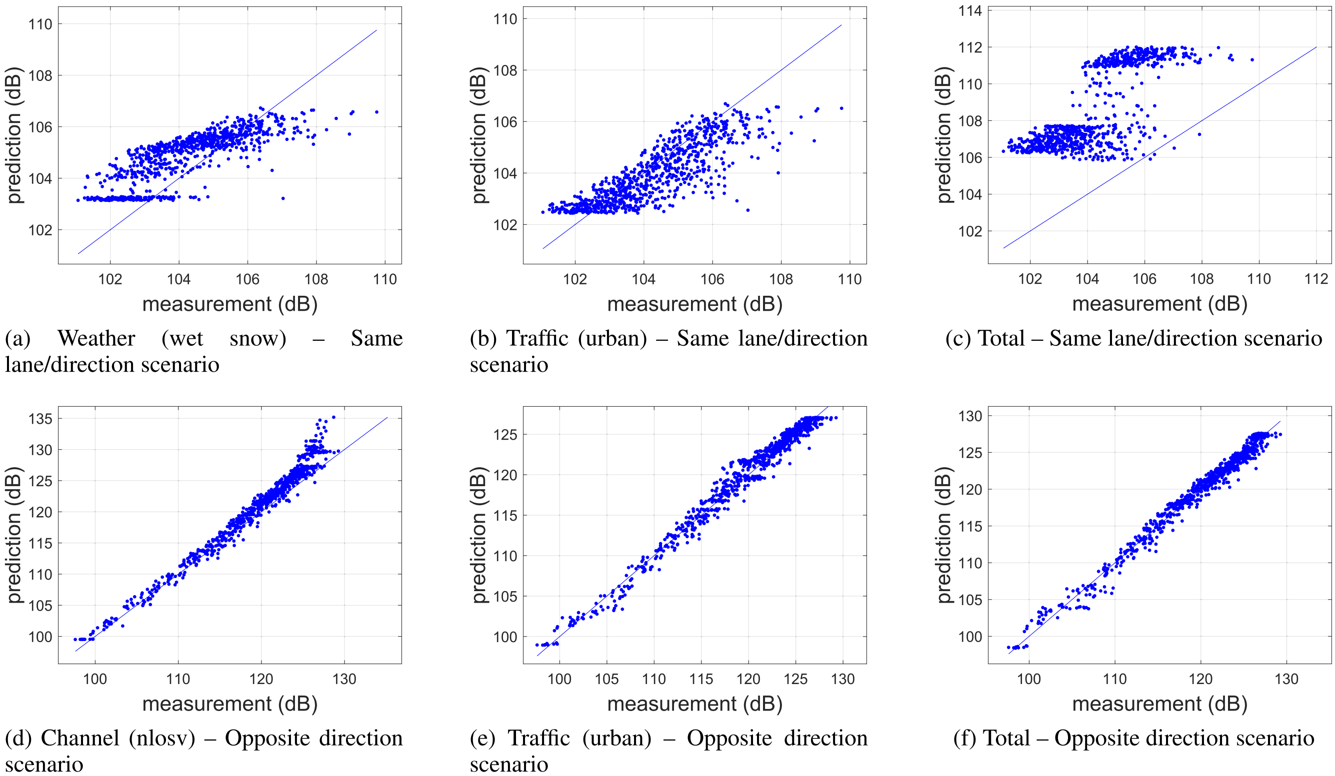
The deep learning model used in the experiment was a DNN, which is commonly used for numerical prediction. The model was trained as part of the path loss data obtained from the simulation, and the remaining data were used for testing.

Because there are no path loss prediction criteria and methodologies considering all parameters of weather, scenarios, and channels, we evaluated the predictive performance of deep learning models by directly comparing the validated simulation data with widely used deep learning-based prediction results. The following are our learning and testing scenarios for evaluating the proposed deep learning model:

We trained deep learning models with rainfall and snowfall data for each weather condition by dividing them into rain and snow under different climate conditions. The training results were tested using the training data, weather, and channel conditions. In terms of scenarios, we trained models with data from highway and urban environments and tested the trained models with data from weather and channel conditions that were excluded from the training data. In terms of channels, we trained three models with data from loss, NLOS, and NLOSv situations and tested the trained models with data from weather and scenario conditions excluded from the training data. Finally, we made the model learn based on all data from the experiments and repeated the above tests. The experimental results are illustrated as tables and graphs in this section.

To reflect the dramatic precipitation and vehicle environment, we used test data reflecting precipitation of 2.5, 20, and 40 mm/h and NLOSv and urban (vehicle-rich environment) simulation data. In addition, we used data obtained from the 30 mm/h precipitation environment as test data.

We selected scenarios using six training data points to verify the prediction performance. In the same lane/direction scenario, the model was classified as wet snow and urban data, and the DNN model learned with the total data to



(a) Weather (wet snow) – Same lane/direction scenario
(b) Traffic (urban) – Same lane/direction scenario
(c) Total – Same lane/direction scenario
(d) Channel (nlosv) – Opposite direction scenario
(e) Traffic (urban) – Opposite direction scenario
(f) Total – Opposite direction scenario

FIGURE 5. Scatter plots for prediction results compared to the measured values of each DNN model according to the training data type. (a) , (b), and (c) are prediction results for same lane/direction scenario, (d), (e), and (f) for opposite direction scenario.

verify the predictive performance in wet snow and urban environments, which are scenarios where rain and snow can be considered together.

In FIGURE 5–12, we investigate the path loss prediction performance by learning a total of six proposed prediction models for data classified by type obtained in the representative scenarios. The scenarios are largely divided into the same lane/direction scenarios and opposite lane scenarios.

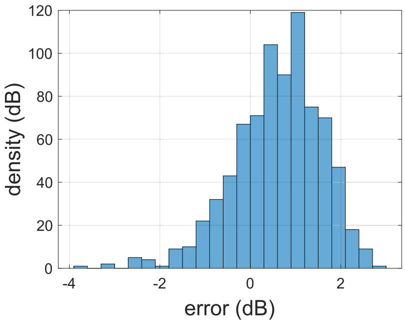
The comparison between the path loss results obtained through the simulator and the DNN-based path loss prediction results is shown in FIGURE 7–12. In the same lane/direction scenario, we had the models learn separately from the data classified as wet snow and the data classified as urban, and the models learned through the total data. FIGURE 7–9 illustrate the path loss prediction results for the same lane/direction scenario. FIGURE 7 and 8 show the results learned only with data classified under certain conditions and show better prediction results than those in FIGURE 9 learned with the total data. In FIGURE 7–9, we analyzed the path loss based on distance because it is a path loss for vehicles driving at different speeds in the same lane/direction.

In FIGURE 10–12, the path loss is schematized based on the sequence of simulations to confirm the path loss when vehicles driving towards each other gradually approach from a long distance and then gradually move away.

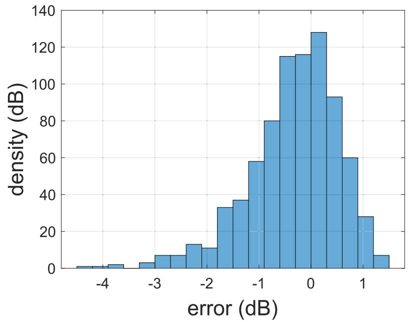
The scatter plots of the prediction results in the same lane/direction scenarios are shown in FIGURE 5 (a), (b), and (c), and the error distributions are shown in FIGURE 6 (a), (b), and (c). The closer the scatter is to the diagonal of the graph, the smaller the error in FIGURE 5. Also, in FIGURE 6, The closer the density is to zero, the higher the prediction accuracy. In the case of path loss in the same lane/direction, the distance gradually increased. Therefore, we expected it to be difficult to find a correlation with the path loss of each parameter for the total learning data in a situation where the change was not severe. Prediction models learned from data extracted only from wet snow environments in the same lane/direction predicted relatively high path loss compared to measurements, whereas models learned only from urban areas predicted relatively low path loss compared to measurements.

In addition, the prediction error was the lowest because attrition, which occurs largely in urban environments, has a high correlation with path loss in the same lane/direction scenario, as shown in FIGURE 6 (b).

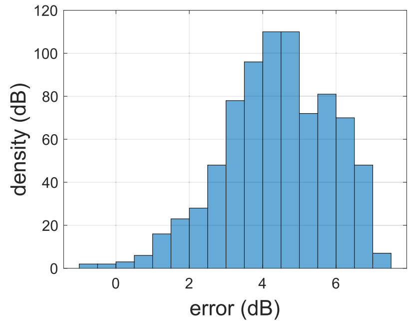
Therefore, as shown in FIGURE 5, the prediction performance is better when learned from the data on road and weather conditions than when learned from the total data. This means that when predicting path loss in the same lane/direction, the model can better predict the characteristics of the data when it is learned by collecting and learning



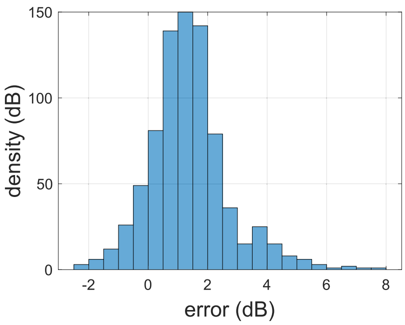
(a) Weather (wet snow) – Same lane/direction scenario



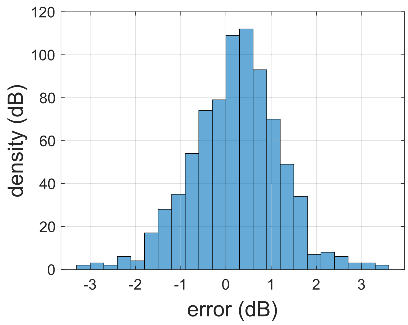
(b) Traffic (urban) – Same lane/direction scenario



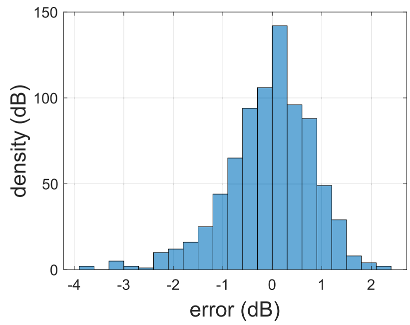
(c) Total – Same lane/direction scenario



(d) Channel (NLOSv) – Opposite direction scenario



(e) Traffic (urban) – Opposite direction scenario



(f) Total – Opposite direction scenario

FIGURE 6. **Error distribution diagrams by prediction results of DNN model according to training data type. (a) , (b), and (c) are prediction results for same lane/direction scenario, (d), (e), and (f) are prediction results for opposite direction scenario.**

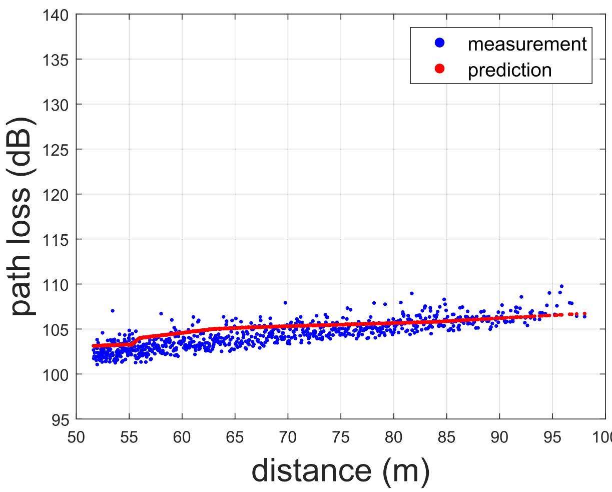


FIGURE 7. **Comparison of path loss data simulated and predicted through DNN model trained with weather data (wet snow) – Same lane/direction scenario.**

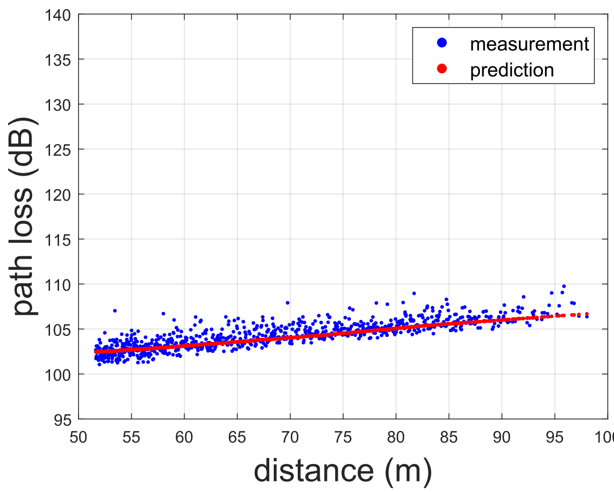


FIGURE 8. **Comparison of path loss data simulated and predicted through DNN model trained with traffic (urban) data – Same lane/direction scenario.**

the characteristics of the data rather than understanding the characteristics of the total data combined in various scenarios.

In the opposite lane scenario, three prediction models were learned separately from data classified as NLOSv, data classified as a city, and the total data to determine prediction performance in urban environments with more vehicles encountered as the distance reduced. We observe the path loss is proportional to the distance as the distance between vehicles gets closer first and then farther apart in this scenario. As shown in FIGURE 10–12, there is more noise because the distance is affected more by weather, channel, and road conditions.

The performances of the three DNN-based prediction models can be used to predict measurements with high accuracy.

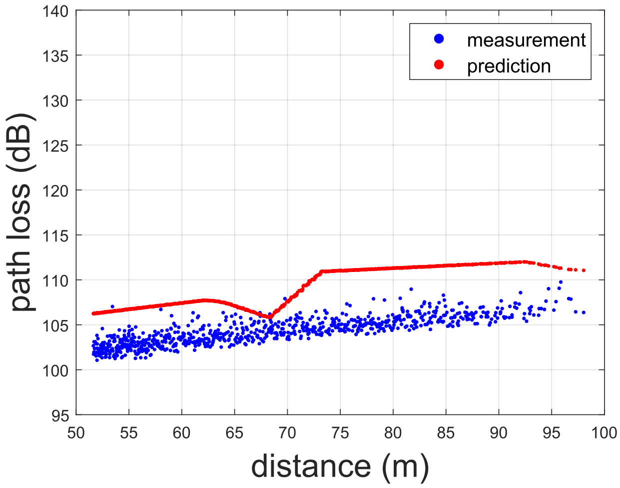


FIGURE 9. Comparison of path loss data simulated and predicted through DNN model trained with total data – Same lane/direction scenario.

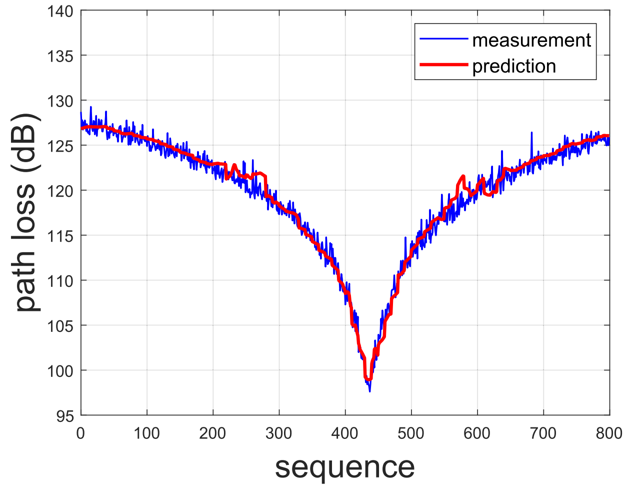


FIGURE 11. Comparison of path loss data from simulation and predicted through DNN model trained with traffic (urban) data – Opposite direction scenario.

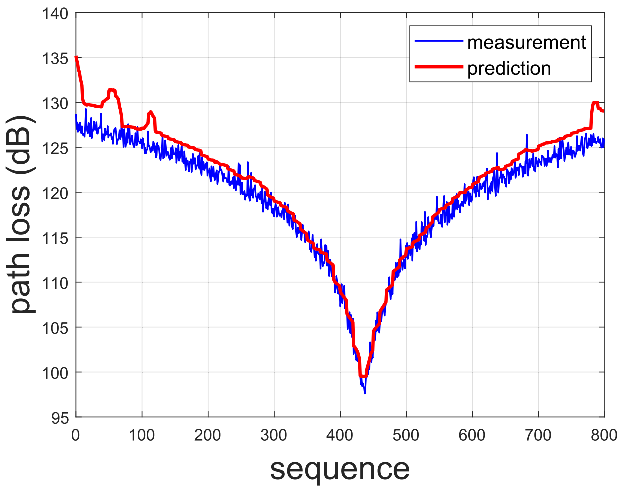


FIGURE 10. Comparison of path loss data simulated and predicted through DNN model trained with channel (NLOSv) data – Opposite direction scenario.

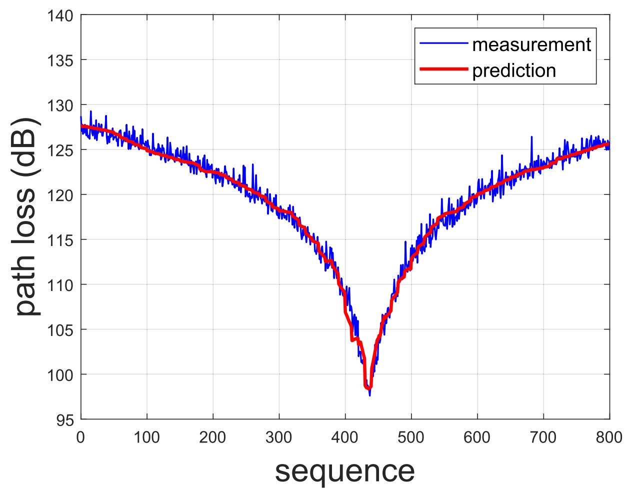


FIGURE 12. Comparison of path loss data from simulation and predicted through DNN model trained with total data – Opposite direction scenario.

Models learned from NLOSv data are rarely affected by the effects of surrounding vehicles at real distances and are heavily influenced by NLOSv at close distances; however, the DNN model predicts that they will have a higher path loss than measurements at long distances. Given the NLOSv classification data characteristics for learning the DNN model, predictions at close distances may be considered reasonable; however, predictions at long distances show a rather low prediction accuracy.

However, the predictions of models learned through urban and total data show high levels of prediction, both long and close. Among them, the prediction of the total data shows a prediction that is close to the measurement. This means that the proposed prediction model makes robust predictions for path loss based on the dynamic distance, weather, channel, and road conditions.

TABLE 3. Path Loss Prediction Accuracy Metrics of each DNN model trained by Learning data type.

Learning data type	RMSE	MAPE	MAE	MaxPE	ESD
Wet snow- Same Lane/Direction	0.9481	1.1455	0.9128	3.8146	1.1463
Urban- Same Lane/Direction	0.6858	0.9280	0.6542	4.4726	0.9285
Total- Same Lane/Direction	4.3956	4.6270	4.2146	7.1894	4.6299
NLOSv- Opposite Direction	1.5341	1.9243	1.2625	7.6731	1.9255
Urban- Opposite Direction	0.7837	0.9993	0.6617	3.5620	0.9999
Total- Opposite Direction	0.8741	0.5614	0.6610	3.7688	0.8747

As a result of comparing the performances of the evaluated DNN algorithms, TABLE 3 shows a comparison of the major performance indicators used to evaluate the accuracy of the proposed path loss prediction model. As shown in the above path loss scatter plots and error distribution diagrams, for same lane/direction, the model learned using data classified Urban predicted with the highest prediction accuracy, for opposite direction, the model learned using data classified Urban and Total data predicted the highest prediction accuracy.

We have made our path loss analysis simulation testbed[5] and DNN-based path loss prediction model[6] *publicly available* on GitHub repositories.

VII. CONCLUSION

This paper presents a novel path loss prediction approach based on deep learning to predict path loss in NR V2V communication using mmWave. The proposed approach differs from existing literature in that it considers all weather, channels, and traffic. Furthermore, additional NLOSv models were included in urban environments with relatively large vehicles to obtain data for deep learning, and data were collected by varying the precipitation from 0 to 25 mm/h for realistic consideration of path loss prediction degradation in bad weather conditions. The collected data led to the DNN, and the test data used some of the collected data that were not used for learning.

We modeled the propagation environment for weather conditions and propagation channels, and integrated them with deep learning algorithms to predict the path loss. To compare the predictive performance of the DNN, training and testing procedures were performed using path loss datasets derived from simulation results considering 5G NR at 60 GHz. The results indicated that the DNN algorithms provided low statistical errors.

Our approach improves practicality by allowing the development of adaptive models over traditional ones that require specific modeling of transceiver distances and obstacles in real-world driving environments where multiple situations are complex. The proposed prediction method can address the problem of path loss prediction degradation in communication caused by weather and channel state in highway and urban environments. The proposed approach is expected to be used for designing wireless communication systems to find accurate and reliable predictive models for weather, channels, and road environments, and help reduce the cost of measurement and save time in real engineering applications.

In future work, we plan to enable path loss prediction for more V2X communication scenarios, such as V2V, vehicle-to-infrastructure (V2I), and vehicle-to-pedestrian (V2P) communication in the field. For example, the proposed deep learning model can be trained using data from real-world vehicle environments that can set specific weather, channels, and traffic conditions and enable path loss prediction in base station-to-vehicle communication. This optimizes the transmission power of uplink and downlink communication and enables adaptive transmitter modeling optimized for output power. We plan to study the problem of predicting path loss in V2I and V2P communication simulation environments using the proposed path loss prediction model and simulation techniques presented in this paper.

[5]https://github.com/sangmosung/path-loss_simulator/

[6]https://github.com/sangmosung/path-loss_pred_DNN/

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