# Predicting Channel Quality Indicators through Deep Learning: A Location-Aware Approach Utilizing Limited Network Parameters

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***Abstract*— In the dynamic landscape of vehicular communication environments, adequate resource allocation and management are critical for ensuring seamless communication, particularly in scenarios involving constantly moving vehicles. To efficiently allocate resources, the base station requires real-time Channel State Information (CSI) from devices. Consequently, vehicles must continuously report their Channel Quality Indicator (CQI) to the base station. The base station, relying on the reported CQI, determines the Modulation and Coding Scheme (MCS). This study introduces a context-aware CQI prediction framework utilizing bidirectional Long Short-Term Memory (Bi-LSTM) techniques. A distinguishing feature of this framework is the strategic incorporation of location information, precisely latitude and longitude, and two key network parameters, namely Received Signal Strength Indication (RSSI) and Reference Signal Received Power (RSRP), tailored to adhere to IEEE 802.11p Wireless Access in Vehicular Environments (WAVE) standards. The simulation results demonstrate the superiority of the proposed scheme, showcasing lower Mean Squared Error (MSE) when compared to alternative methods and previous studies. This strategic inclusion of geographical data not only highlights the model's adaptability to spatial dynamics but also positions it as a comprehensive solution for accurate CQI prediction, thereby contributing to the efficiency of resource management in intelligent transportation systems.**

***Keywords*— V2X, bidirectional long short-term memory (Bi-LSTM), Channel quality indicator (CQI), deep learning, location-awareness, Beyond 5G/6G.***

## I. Introduction

In recent years, the progress in vehicle-to-everything (V2X) communication has become pivotal for intelligent transportation systems (ITSs), encompassing various wireless technologies like vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-pedestrian (V2P), interactions with vulnerable road users (VRUs), and cloud network connectivity (V2N) [1]. This evolution aims to integrate V2X into 6G wireless systems [2], positioning it as a vital component of ITSs. The primary technologies driving V2X communications are dedicated short-range communication (DSRC)-based vehicular networks and cellular-based vehicular networks [3], with DSRC standards like IEEE 802.11p for WAVE and IEEE 1609.1.4 playing a foundational role [4].

The efficacy of V2X communication systems relies on the dynamic nature of wireless channel responses, particularly in high-mobility scenarios. V2X communication is instrumental in delivering reliable, low-latency services for vehicles in applications like forward collision warning, road safety, and emergency stops. Meeting stringent requirements for real-time applications, such as less than 5ms end-to-end latency for 1600-byte messages with a 99.999% probability of success, is imperative. Traffic patterns involve event-driven and periodic messages at a 100ms interval, supporting speeds up to 500 km/h in highway scenarios [5]. Meeting these demanding requirements necessitates a profound understanding of the wireless channel characteristics, and this understanding must be seamlessly integrated into communication protocols. Therefore, efficient radio resource management by the base station (BS) becomes paramount. To achieve this, the BS requires accurate CSI from the devices, encompassing path loss, amplitude, and phase characteristics. However, obtaining precise CSI in fast-fading environments poses a significant challenge. Consequently, the BS solicits CQI from the devices, which encompass radio parameters such as RSSI, RSRP, reference signal received quality (RSRQ), and signal-to-noise ratio (SNR) [6].

CQI, calculated through a straightforward formula based on radio signal strength, provides valuable insights into the channel characteristics. Subsequently, the BS leverages the reported CQI from vehicular devices to determine the MCS. This decision significantly impacts throughput, as the MCS combines modulation and code rate adjustments according to the prevailing channel conditions.

In the context of 5G and upcoming communication systems designed to support V2X, the integration of precise location information emerges as a valuable asset for wireless network design and optimization [7]. The attenuation of the SNR with increasing distance, attributed to path loss, underscores the importance of leveraging location data for estimating received power and assessing interference levels. Notably, 5G user terminals exhibit predictable mobility patterns primarily associated with individuals or fixed and controllable entities. This predictability enhances the utility of location information in optimizing network performance. The strategic utilization of precise location information thus becomes integral for improving the efficiency and functionality of future communication networks[8].

In addition, recent endeavors have explored harnessing the potent capabilities of cutting-edge machine learning (ML) and deep learning (DL) models across various domains, such as computer vision [9], signal identification [10], prediction [11], and multiple fields of wireless communication [12]. The capacity of deep learning models to uncover intricate relationships among numerous features has led to their application in crucial real-world communication scenarios, including traffic classification, network slicing, MIMO signal classification, handover, and mobility predictions. ML and DL-based CQI predictions [13] and [14] exemplify such innovative approaches.

Therefore, this paper advantageously leverages the significance of location information and the efficacy of DL technologies, with a specific focus on harnessing the capabilities of bidirectional long short-term memory (Bi-LSTM) for CQI prediction in vehicular communications. The adoption of Bi-LSTM is motivated by its unique capacity to comprehend bidirectional dependencies in sequential data, a critical aspect in modeling the dynamic characteristics of wireless channels in vehicular communication. The paper proposes a DL model that predicts CQI based on device location and two essential network parameters (RSSI and RSRP) tailored for swiftly changing channels in the moving environment. This location-aware RSSI and RSRP-based CQI prediction aims to decipher channel characteristics, ultimately enhancing communication performance in 5G and beyond networks.

## II. Related Studies

Maintaining stable transmission for safety in vehicular communication is challenging due to frequent channel variations. Recent studies indicate that ML/DL techniques outperform traditional signal processing methods in predicting CQI and CSI, offering a promising solution for addressing this challenge.

Liu et al. [15] introduced an intelligent connected vehicle system that enhances resource management and communication by predicting radio channel parameters. Their LSTM-based channel prediction model uses historical CSI, estimated through Rayleigh fading distribution. However, relying solely on statistical models for real-world channel analysis may introduce errors.

Another recent investigation [14] focused on mitigating the CQI feedback delay through the application of traditional ML techniques and evolutionary computing. This study, uniquely designed to operate at the user equipment (UE) side, stands out by eliminating the need for alterations in signaling protocols between the gNB (Next Generation NodeB) and UE, thereby avoiding any undue burden on the base station. However, a notable limitation of this study lies in its challenge to incorporate updated SINR values, encompassing a spectrum of UE and network parameters.

Zeng et al. [16] proposed a connected-V2X channel estimation model using a spectrum segmentation filter and shifting technique. Their system predicts CQI based on SNR calculation from the received signal, showing enhanced accuracy at 300 km/h. However, the SNR-based CQI relies on estimating CSI from OFDM symbols, introducing complexity and computational challenges in high-speed, fast-changing channels. A related study [17] proposed a lightweight LSTM-based CQI feedback scheme for IoT devices. However, while this approach reduces feedback overhead compared to periodic schemes, it is limited to stationary IoT scenarios and lacks consideration for device mobility. A study similar to ours [13] employed an LSTM model with RSSI as the sole network parameter. Despite achieving promising results, with RMSE above 40%, the study did not address the constant mobility of vehicular devices, overlooking a crucial aspect in dynamic environments.

## III. System Model

This section furnishes essential background details on LSTM and introduces the significance of channel quality indicators estimation in wireless communication systems.

### A. Bidirectional Long Short-Term Memory (Bi-LSTM) model

Long Short-Term Memory (LSTM) is categorized as a recurrent neural network (RNN) and utilizes a sequence of units featuring input, forgetting, and output gates alongside a state unit. These integral components enhance the facilitation of information flow, endowing the network with the capability to address issues associated with long-term reliance that are prevalent in generic RNNs. LSTMs are adept at overcoming challenges such as gradient disappearance and explosion. [18]. Bidirectional Long Short-Term Memory (Bi-LSTM), a subtype of RNN, is designed to process sequential data in both forward and backward directions. By combining the strengths of LSTM with bidirectional processing, Bi-LSTM captures both preceding and succeeding contexts within the input sequence. It consists of two crucial components: an LSTM structure for forwarding information and another for backward transmission. Bi-LSTM is frequently employed in tasks such as modeling context information and text classification [19], offering a notable advantage in comprehending intricate dependencies within the input sequence.

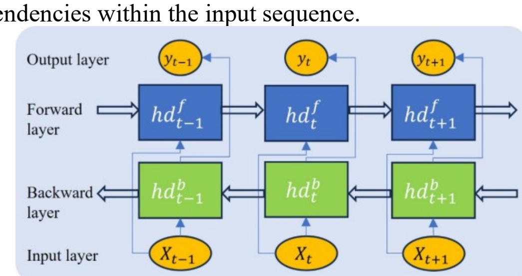


Fig. 1. Bi-LSTM structure

Its notable advantage lies in capturing the context preceding a specific time step, as seen in traditional RNNs and the subsequent context. This dual consideration of past and future information allows Bi-LSTM to comprehend more intricate dependencies within the input sequence [20]. The bidirectional nature of LSTMs proves effective in capturing long-term dependencies in sequential data by processing input sequences both forward and backward. Additionally, the flexibility of bidirectional LSTMs allows for customization by adding extra layers, like convolutional or attention layers, thereby enhancing performance.

In Fig. 1, the forward hidden state $hd_t^f$ at the time $t$ is obtained in the following way:

$$hd_t^f = sigmoid(\overline{\Psi}_f I_t + \overline{\varpi}_f hd_{t-1}^f + \beta_f) \tag{1}$$

$\overline{\Psi}_f$ and $\overline{\varpi}_f$ are forward weight values and $\beta_f$ are forward deviation values.

The hidden backward state $hd_t^b$ at time $t$ is defined in the following ways:

$$hd_t^b = sigmoid(\overline{\Psi}_b I_t + \overline{\varpi}_b hd_{t-1}^b + \bar{\beta}_b) \tag{2}$$

where, $\overline{\Psi}_b$ and $\overline{\varpi}_b$ are backward weight values and $\bar{\beta}_b$ is backward deviation value.

When at time $t$, the output value $y_t$ can be defined in the following ways:

$$y_t = Q_f hd_t^f + Q_b hd_t^b + \bar{\beta} \tag{3}$$

where $Q_f$ and $Q_b$ are weight values and $\bar{\beta}$ is a deviation value.

The choice of Bi-LSTM is motivated by its distinctive capability to consider the context from both past and future time steps simultaneously. This bidirectional processing proves advantageous in scenarios where the efficacy of vehicular communication systems heavily depends on anticipating and adapting to rapidly changing channel conditions. These attributes render Bi-LSTM particularly well-suited for wireless network channel prediction, especially in CQI prediction.

### B. Proposed Bi-LSTM-based CQI Prediction

The provided model comprises a CQI definition rooted in real-time location information alongside RSSI and RSRP values gathered from the communication environment between vehicles and infrastructure. A deep learning architecture, specifically a three-layer Bi-LSTM network, is proposed for predicting these parameters. This model is expressly crafted to deliver swift responses in the dynamic context of vehicular communication channels.

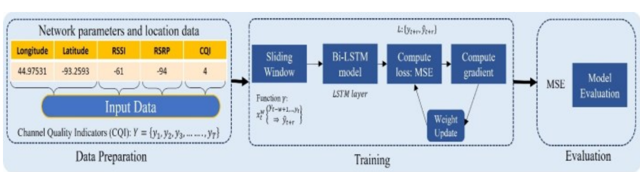


Fig. 2. Data prediction system using a Bi-LSTM model

Fig. 2 visually outlines the CQI prediction algorithm proposed in this study, with the model leveraging a Bi-LSTM network. The proposed deep learning structure is fine-tuned for optimal CQI prediction in vehicular communication by optimizing network parameters like layers, hidden units, and input data intervals. The CQI, comprising received signal information, serves as input to the prediction model, and Table 1 details the network configuration and training parameters. The resulting optimal LSTM network encompasses input gates, forget gates, output gates, and memory cells, enhancing the accuracy of CQI predictions in vehicular communication scenarios.

## IV. Experiment

The evaluation of the proposed model involves computing the variance between the predicted and actual locations at each time step, with mean square error serving as the performance metric for Bi-LSTM models in this research. The initial section of this segment introduces the experimental setup and environment, providing context for the subsequent assessment indicators of the evaluation model. Following this, the proposed model is compared with alternative studies to gauge its effectiveness.

### A. Dataset

The Lumos5G [21], [22] constitutes a fundamental asset for an extensive investigation into the dynamics of 4G/5G networks. Derived from a meticulous measurement study conducted in a major U.S. city, this dataset zeroes in on the throughput of commercial mmWave 5G services as experienced by applications running on UE. The dataset, crafted through a series of comprehensive experiments and rigorous statistical analyses, sheds light on critical factors on the UE side that significantly impact 4G/5G performance. Detailed information about the Lumos5G dataset is available in [19]. From this dataset, we get our expected features like longitude, latitude, RSSI, and RSRP, and by using RSSI values, we generate the CQI value by considering the referenced information from [23].

### B. Experiment Setup:

The investigations detailed in this article were conducted using a consistent computer configuration, featuring an Intel® Core™ i7-8700 CPU @3.20GHz ×12 Processor, 16GB RAM, and NVIDIA GeForce RTX20270 GPU and operated on the Windows 10 platform. The computing provisions ensure a robust foundation for conducting our investigation. The CQI prediction experiments were implemented using Python 3.9. Data points were organized in a time sequence to construct a time series called CQI prediction data, incorporating latitude and longitude information and corresponding RSSI, RSSP values, and associated CQI values.

The Lumos5G dataset, consisting of 65118 rows with the mentioned features, allocated 47,000 rows for model training, 14,494 for validation, and the remaining for testing the CQI prediction model. The training process involved using the training set initially, followed by validation set input for model validation, and finally, the test set for prediction. The models' predictive performance was assessed by analyzing errors between actual CQI data in the test dataset and predicted CQI data.

The sliding window method was adopted for handling input data in the experiments, with a window size set to 20. This means data at every twenty-time point served as input, moving one time point at a time, forming the tensor of the input model. The reshape function converts Time series data into the required format, resulting in 3D tensors (samples, timesteps, features). Consequently, the input and output shapes for the training dataset were (47000, 20, 3) and (47000, 1), respectively. For the validation and test datasets, the shapes were (14494, 20, 3), (14494, 1), and (3624, 20, 3), (3624, 1), respectively. The Lumos5G dataset, reflective of real-world conditions, was the foundation for the investigations. The experimental data for training the model were normalized for input data convenience and inversely normalized for visualizing results. The chosen optimizer was Adam, with the epoch set to 20 to enhance the training process.

### C. Evaluation Metrics

MSE is the prevalent metric used for evaluating regression problems, and our proposed model's performance is measured using this metric. The formula for computing the final evaluation indicators is detailed in the following equations:

$$MSE = \frac{1}{NUM}\sum_{t}\left(y_{pred}(t) - y_{real}(t)\right)^2 \tag{4}$$

This equation $y_{pred}(t)$ represents the predicted CQI value at a time $t$ , while $y_{real}(t)$ signifying the actual CQI value at a time $t$ . The MSE metric's lower values indicate a closer proximity of the predicted CQI values to the actual ones, indicating a higher degree of prediction accuracy achieved by the model.

### D. Implementation Process

Implementation of the Bi-LSTM model for predicting CQI in vehicular communication involves four distinct steps: data preprocessing, model construction, model training, and future value prediction. Fig. 2 shows the whole model implementation process and prediction of the CQI.

Initially, data preprocessing is executed, encompassing tasks such as handling missing values and outlier removal and employing the sliding window method to transform time series data into input-output pairs. Each input aggregates data from multiple time steps. At the same time, the output represents the value of the subsequent time step, facilitating the conversion of time series data into a format conducive to model training.

Subsequently, the Bi-LSTM model is constructed, featuring one input layer, three Bi-LSTM layers, and one dense layer. This architecture is designed to facilitate the training and prediction of CQI using the Lumos5G dataset.

The third step involves model training, where the training data is utilized to optimize the weight and deviation of each model. Forward and backward passes on the training data calculate the gradient of the loss function, and the Adam optimization algorithm is employed to iteratively update the model's parameters, minimizing the loss function. This process is repeated until the model's loss function converges or reaches a predetermined number of training iterations.

## V. Results and Discussions

The proposed Bi-LSTM model is architecturally designed as a sequence of layers, each playing a crucial role in the model's overall functionality. The layer arrangement comprises three bidirectional LSTM layers, featuring eight units in each layer, followed by a dense layer with a single output unit.

In the bidirectional LSTM layers, eight units are incorporated into each layer, instilling a bidirectional capability that enables the model to capture past and future dependencies in the input sequence.

TABLE I. Bi-LSTM parameters for CQI predictions

| **Bi-LSTM network** | **Parameters** |
|---|---|
| Layer | Input,<br>Bidirectional LSTM,<br>Dense layer,<br>Output regression |
| Hidden units | 8, 8, 4 |
| Maximum epoch | 20 |
| Cost function | Mean squared error (MSE) |
| Learning rate | 0.001 |
| Dropout rate | 0.0 |
| Recurrent drop out | 0.0 |
| Optimizer | Adam |

Batch normalization layers are strategically placed after each bidirectional LSTM layer, contributing to the stabilization and acceleration of the training process. The final dense layer, with a single unit, functions as the output layer, producing a singular output essential for the model's predictive task. The model encompasses 4,177 parameters, of which 4,081 are trainable and 96 are non-trainable.

Throughout the training phase, the model is fed with batches of 47,000 examples, each characterized by a sequence length of 20 timesteps and three features. The training process iterates for 20 epochs, signifying the number of times the complete training dataset undergoes processing by the model. Dropout and recurrent dropout, set to 0.0, indicate that no dropout regularization is incorporated during training.

### A. Performance of Bi-LSTM

The performance assessment of Bi-LSTM networks involves an evaluation based on MSE and complexity. As illustrated in Fig. 3, the model exhibits a swift convergence with a notably lower MSE loss than the findings in [13] and [24].

The training dynamics of the Bi-LSTM neural network unfold over 20 epochs, each comprising 1469 batches. The duration for the initial epoch is approximately 75 seconds, with a declining trend observed in subsequent epochs, reaching around 64 seconds for the final epoch. The progressive reduction in training loss, from 2.8701 to 0.0143 (Fig. **#), signifies the model's enhanced capacity to minimize the disparity between predicted and actual values over successive epochs. Correspondingly, the validation loss demonstrates a comparable declining pattern, reaching a minimum of 0.0038 (Fig. 3), indicative of the model's adeptness in generalizing well to unseen data.

Further analysis from Fig. 3 reveals a gradual reduction in validation loss, nearing zero after 20 epochs. Additional experimentation with the 25th, 40th, and 50th epochs, incorporating the early stopping method, substantiates that the 20th epoch yields the most favorable outcomes. This underscores the importance of careful consideration of epoch selection in achieving optimal model performance.

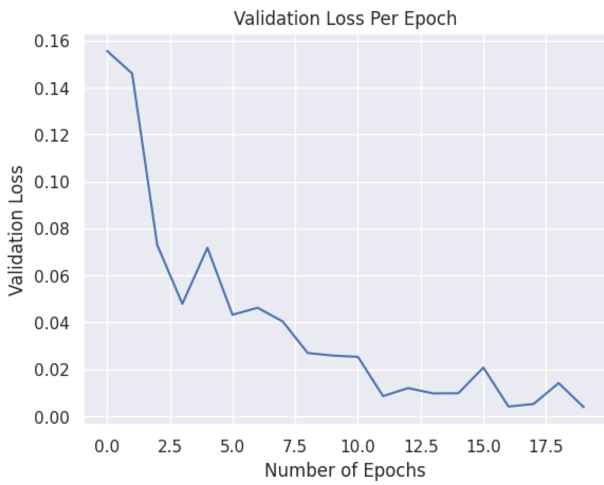


Fig. 3. MSE loss of Bi-LSTM model

The time expended per epoch, from 59 to 68 seconds, indicates the computational efficiency inherent in the training process. This efficiency is underscored by the overall completion of training within 1295.58 seconds, highlighting the Bi-LSTM model's adeptness in discerning temporal dependencies and patterns within the Lumos5G dataset.


Fig. 4. Bi-LSTM model evaluation over training and validation dataset

By examining Fig. 4, it becomes apparent that the training error initially exhibits relatively higher values than the validation loss. However, over the subsequent eight epochs, the training error experiences a gradual decrease until it aligns closely with the validation loss. This convergence between training error and validation loss indicates a stable model training and testing phase, implying the model has successfully learned and generalizes well to new data. This phenomenon is crucial for ensuring the model's robustness and reliability across various scenarios.


Fig. 5. MSE metrics for testing data

Fig. 5 provides a clear depiction of the effectiveness of the proposed model when MSE is employed as the evaluation metric, particularly in comparison to BiLSTM models, for testing data. Notably, in the majority of cases (approximately 3500 instances), the MSE values are less than 0.08. For the remaining testing data, the errors are below 0.25, indicating the model's capability to predict CQI with a high degree of accuracy. This performance surpasses the outcomes observed in other studies, such as [13], [14], [17].

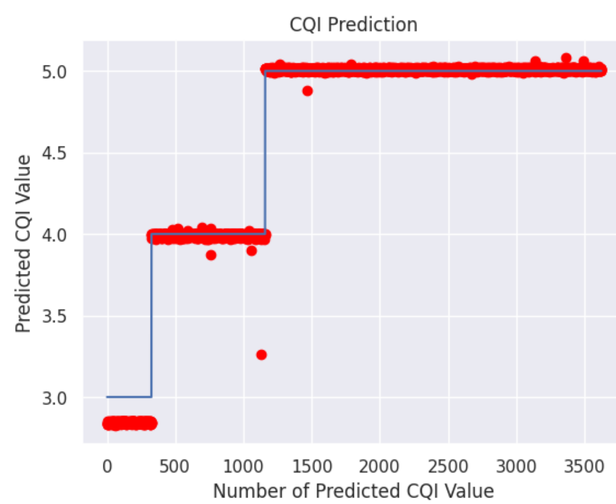


Fig. 6. Prediction of CQI from testing data

The conclusive Fig. 6 depicts the disparity between the original CQI and the predicted CQI. Only four cases exhibit the maximum distance between the predicted and actual CQI. Moreover, the predicted CQI is generally lower than the original values in the testing data range of [0-300]. Still, when considering values greater than 2.5, the predicted CQI aligns closely with the actual CQI. This observation reinforces the model's accuracy in predicting CQI values, particularly in cases where deviations are minimal.

## VI. Conclusions

The proposed Bi-LSTM model is structured to effectively capture temporal dependencies in sequential data, specifically tailored for the context of CQI prediction in vehicular communication environments. The presented architecture balances complexity and performance, as demonstrated by its competitive results regarding Mean Squared Error during training, validation, and testing. An integral aspect contributing to the success of the proposed Bi-LSTM model is the incorporation of key features, with a notable emphasis on location information such as latitude and longitude values. These geographical parameters play a pivotal role in predicting CQI accurately. Incorporating location information as a prominent feature enhances the model's understanding of the complex interplay between communication channels and geographical context, ultimately contributing to its exceptional performance in predicting CQI values. This emphasis on spatial awareness highlights the model's adaptability. It signifies its potential to elevate the reliability and effectiveness of intelligent transportation systems by providing insights into the intricate spatial dynamics of vehicular communication networks.

## Acknowledgment

This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2023-RS-2022-00156353) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation). This work was supported by the Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korean government (MSIT) (No. 2021-0- 00484).

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