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GRU Based MCS Selection in Tactical Vehicle Communication

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Abstract – In this paper, we propose optimal modulation coding scheme (MCS) selection based on Gated Recurrent Unit (GRU) for one-to-one communication between tactical vehicles. The communication between tactical vehicles assumes orthogonal frequency division multiplexing (OFDM) and performs bidirectional communication with time division duplexing (TDD) manner. Since the TDD system uses the same frequency for transmitting and receiving, the bidirectional communication channels are the same. Based on the Signal-to-Noise Ratio (SNR) measuring from the received signal, the MCS at the future transmission time is predicted, utilizing a Gated Recurrent Unit (GRU), which is a type of Recurrent Neural Network (RNN). Existing methods for predicting the MCS from the received SNR include the mean value method and the recent value method, and the method based on the convolutional neural network (CNN). Based on the computer simulation results, the proposed GRU-based RNN technique shows a lower outage probability of communication than all conventional methods while provides the highest throughput.

Keywords – GRU, SNR, MCS Selection, Deep learning, Tactical Communication.

I. INTRODUCTION

The mobile wireless communication is constantly evolving, with new 5G NR, 6G mobile communication and terrestrial tactical communication [1]. In the midst of these ongoing developments, the choice of Modulation Coding Scheme (MCS) has always been an important for the reliability and throughput of the communication. The transmitter should select the most suitable MCS for the channel environments. Selection of MCS decides the efficiency of the frequency resource usage and the reliability of communication. Military communications between tactical vehicles are particularly sensitive to the issue of choosing an MCS. In military communications, where orthogonal frequency division multiplexing (OFDM) and time-division duplexing (TDD) are employed, the MCS is usually selected from the past received channel responses. TDD is a method that divides the reception and transmission by time, and the receiving channel and the transmitting channel are the same because the two channels share the same frequency [2,3]. Therefore, the transmission MCS is commonly selected by observing past received channels [4]. This study adjusts the modulation scheme through a Channel Quality Indicator (CQI) feedback system, reflecting current channel quality. It focuses on appropriately adjusting the data transmission rate depending on whether channel conditions are good or bad, thereby enhancing the overall performance and reliability of the communication system. Research continues in current mobile wireless communications to achieve high transmission rates [5] and minimize the bit error rate [6,7]. As evidenced by previous studies, it is widely acknowledged that the most crucial aspect of MCS selection is understanding the current quality of the channel. The most commonly used information to assess the current channel state is the Signal-to-Noise Ratio (SNR) of the received signal. In the past, MCS was selected by methods such as exponential effective Signal-to-interference-plus-noise ratio (SINR) mapping or averaging the SNR [8, 9]. Those methods are currently used in Internet of Things (IoT) communications [10]. In military communications, MCS is also selected by observing only the SNR of the most recently received signal. Recent advances in artificial intelligence have led to research that attempts to use artificial intelligence to select the MCS [11]. The research in [11] used a convolutional neural network (CNN) to predict the optimal MCS for the future transmission. Simulations demonstrated that the artificial intelligence (AI) model was more accurate than traditional rule-based methods.

In this paper, we propose use of Recurrent Neural Network (RNN) for MCS selection by exploiting the fact that the SNR information of the received signal is time series data. It is well known that RNN models are advantageous for making predictions with timely correlated data [12,13]. The proposed method is to predict the SNR at the time of transmission through an RNN regression model and select the MCS based on the predicted SNR. The RNN we use is a Gated Recurrent Unit (GRU), which is a type of Long Short-Term Memory (LSTM) designed to solve the problem of long-term dependence [14]. In a TDD environment, the fast operation of GRUs compared to LSTMs is more suitable because the switching between transmitting and receiving is fast. Previous studies have shown that the performance of GRUs is not significantly degraded compared with LSTMs [15]. The performance evaluation of the proposed GRU-based RNN model is conducted through computer simulations considering both the movement and reorientation of tactical communication vehicles. To evaluate the performance of the proposed model, we adopt the CNN method for predicting future SNR at the transmission time, as described in [11]. The CNN model is adjusted to fit the data of this study and retrained. Additionally, comparisons with existing algorithmic methods are performed. The algorithmic methods used include the average value method and the recent value method. The average value method selects MCS based on the average SNR received over a certain period. The number of received SNR values used to compute the average is determined through experimentation. The recent value method reflects the SNR of the most recently received signal as the predicted SNR at the transmission time. Considering potential signal loss in real-world scenarios, the recent value method selects the most recent successful received SNR. All methods, including the average value method, conventional CNN, and the proposed GRU-based RNN method, account for potential signal loss. Before selecting MCS using each method, the data undergo preprocessing, including interpolation, to account for potential signal loss. Performance evaluation compares the existing and proposed methods in terms of SNR prediction accuracy, Outage Probability, and Throughput. To focus on the performance comparison based on MCS selection, this study assumes a one-to-one communication scenario using only one antenna.

The structure of this paper is as follows: Chapter 2 describes the conventional method for selecting MCS. Chapter 3.1 presents the overall system model based on the proposed RNN artificial intelligence. Chapter 3.2 describes the model structures of the conventional CNN and the proposed GRU-based RNN. In Chapter 4.1, the experimental environment of this study is outlined. Chapter 4.2 conducts a performance comparison of the proposed RNN based on the simulation results, and finally, Chapter 5 concludes the paper.

II. CONVENTIONAL METHODS

Algorithmic Methods

There are two methods for selecting the MCS using algorithms.

Average Value Method

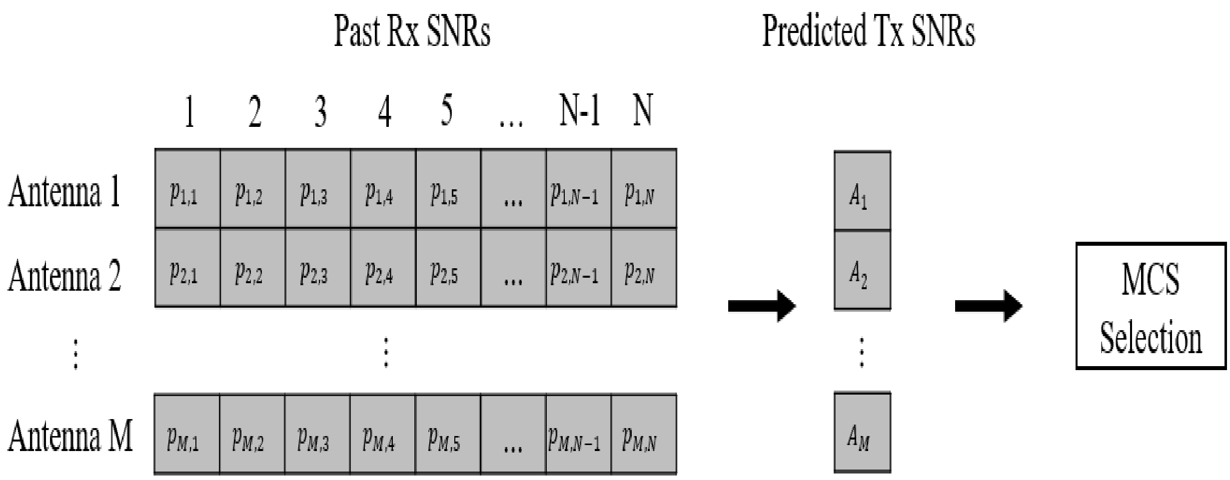

Fig 1. Average Value Method.

The Average value method predicts the SNR at the transmission time by calculating the average of the received signals for each antenna to select the MCS. In **Fig 1**, p represents the past received SNR values. Let M be the number of antennas and N be the number of received SNR values. The average SNR value for antenna m is denoted as A_m. Mathematically, it can be expressed as follows:

$$A_m = \frac{1}{N}\sum_{i=1}^{N} p_{m,i} \; (1 \le m \le M) \tag{1}$$

The calculated value of A_m is used to predict the SNR value of the respective antenna at the time of transmission, and the MCS is selected accordingly.

Recent Value Method

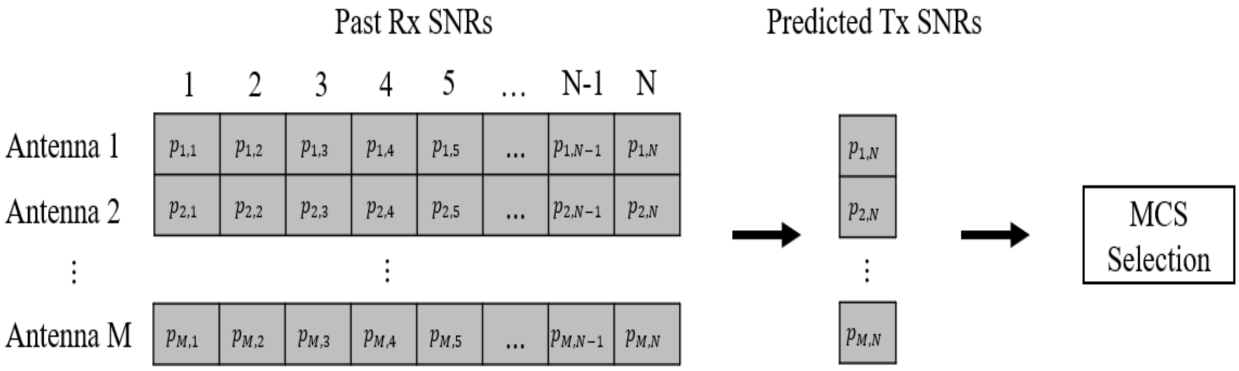

Fig 2. Recent Value Method.

The Recent Value method predicts the SNR at the transmission time by using the most recent received signal value for each antenna to select the MCS. This method assumes that, given the SNR information is time-series data, the most recent received signal's SNR will be the most similar to the SNR at the time of transmission. Among algorithmic methods, it has a low complexity and relatively high accuracy. **Fig 2** shows recent value method.

Artificial Intelligence Methods

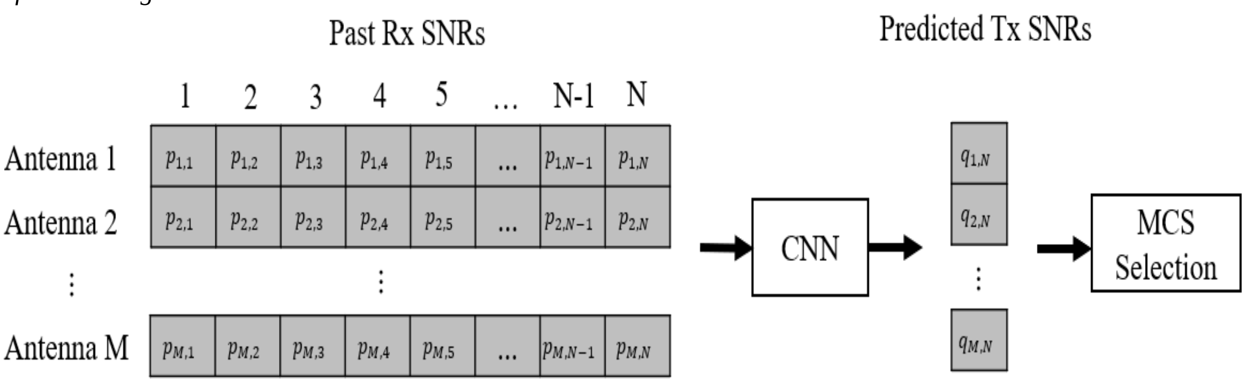

Fig 3. Convolutional Neural Network Method.

Fig 3 illustrates the method of MCS selection using CNN. This diagram is based on the approach introduced in a previous study [11], where *q* represents the predicted value from the artificial intelligence, i.e., the output of the model. In that study, experiments were conducted with *N* values ranging from 10 to 100 to determine the optimal *N*. Similarly, this paper will derive the optimal *N* value to compare it with the proposed optimal existing CNN method. However, considering that the received SNR information is time-series data, the proposed RNN method is more suitable than the CNN, which excels in image processing.

III. PROPOSED METHODS

System Model

The MCS selection system model based on the received signal SNR proposed in this study is as follows.

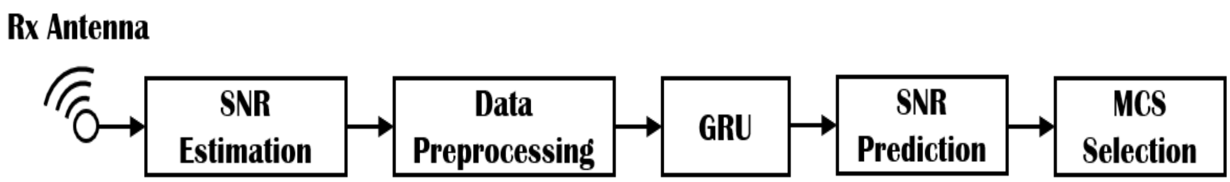

Fig 4. MCS Selection System Block Diagram.

Fig 4 presents a block diagram illustrating the process of selecting the MCS from the reception to the transmission of a signal, with the detailed process as follows. The signal received by the antenna first undergoes an SNR estimation stage. SNR is estimated at regular intervals of OFDM symbols, and a total of N data points are sequentially arranged according to time steps. Therefore, the data containing SNR information forms an M * N matrix, where M represents the number of antennas. Through experimentation, the optimal value of N is determined and used as input for the artificial intelligence. The method of selecting MCS based on the average SNR of the received signals also seeks to find the optimal value of N through experimentation for averaging. In the method that uses the SNR of the most recently received signal, the value of N does not influence the outcome.

The second step is to preprocess the data. In the real world, there are situations where signals are not received. In this case, the SNR of the unreceived timestep is filled in by interpolation using the neighboring received SNRs. The linear & edge zero interpolation method is used to interpolate, and the specific method is as follows. Unreceived timesteps between two received SNR values are linearly interpolated to fill in the SNR values. Timesteps that are on the left or right edge of the data matrix and do not fall between the received SNR values are interpolated to zero. If the most recent SNR is 0 dB when using the recent value method, it will traverse the previously received SNRs and use the most recent non-0 dB SNR. The data matrix, after the interpolation process, takes the shape as shown in **Fig 5**. In this paper, it is assumed that the number of antennas (M) is one.

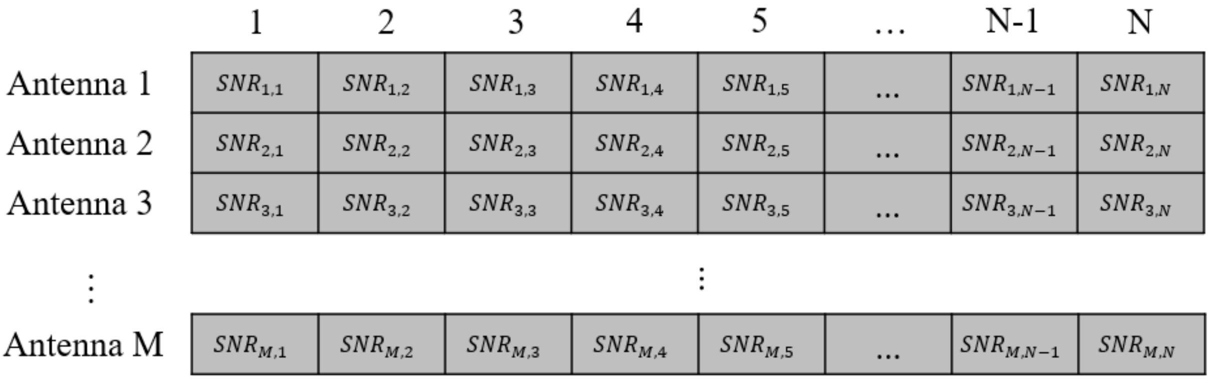

Fig 5. Interpolated Input Data Matrix.

Thirdly, as depicted in **Fig 5**, the interpolated SNR data are fed into a GRU-based artificial intelligence. The GRU model, trained as a regression model, predicts the SNR at the time of transmission. Subsequently, MCS is selected based on the predicted SNR by referencing an MCS selection chart, and transmission is initiated. The following **Table 1** illustrates the criteria for MCS selection.

Table 1. MCS Selection Table

Level	Modulation & CTC code rate	Throughput (Mbps)	Threshold SNR (dB)
0	Out of Range		
1	QPSK, 1/3	1.6612	1.4
2	QPSK, 1/2	2.4918	3.9
3	QPSK, 2/3	3.3226	7.1
4	QPSK, 3/4	3.7379	8.0
5	QPSK, 6/7	4.2718	10.3
6	QPSK, 8/9	4.4300	11.3
7	16QAM, 1/2	4.9838	12.6
8	8PSK, 3/4	5.6068	15.5
9	16QAM, 2/3	6.6452	17.3
10	16QAM, 3/4	7.4758	19.5
11	64QAM, 2/3	9.9678	21.2
12	64QAM, 3/4	11.2136	26.7
13	64QAM, 6/7	12.8156	28.3
14	64QAM, 8/9	13.2904	30.6

Model Structure

The structure of the conventional CNN model and the proposed GRU-based RNN model are as follows.

Conventional CNN Model

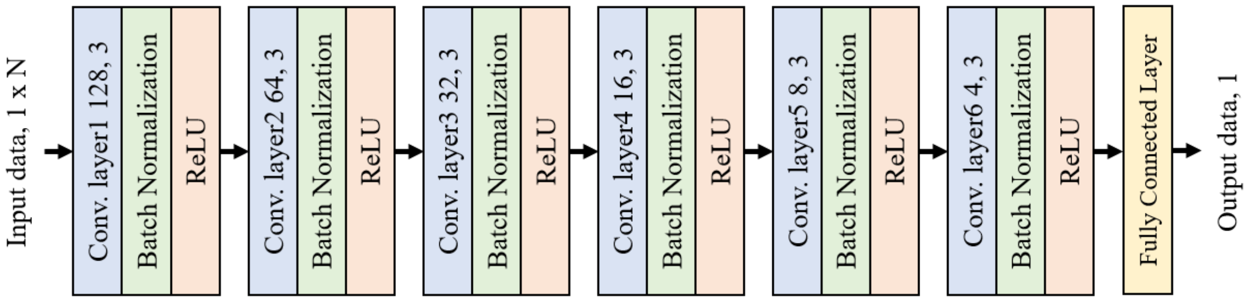

Fig 6. Conventional CNN Structure.

The CNN model structure depicted in **Fig 6** is optimized for this study's data, referencing prior research [11]. It comprises a total of six convolutional layers and a fully connected layer, with each layer consisting of convolution, batch normalization, followed by an activation function in sequence. This regression model takes a $1 \times N$ received signal SNR as input and outputs the predicted SNR at the transmission point. The filter sizes for each layer are 128, 64, 32, 16, 8, 4, resulting in a reduction of the output channel count after each layer.

Proposed GRU Based RNN Model

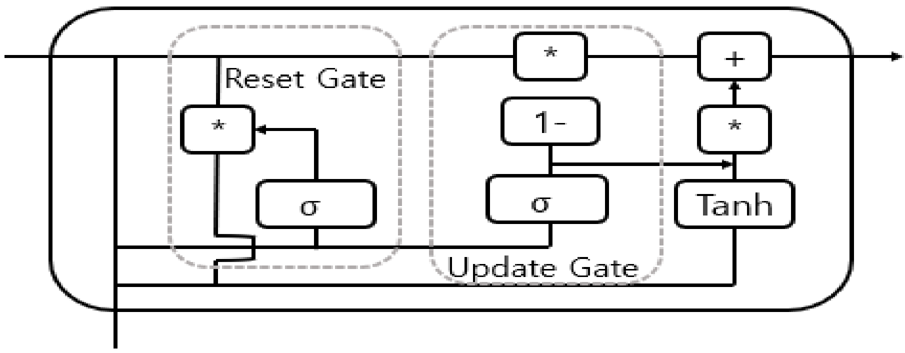

Fig 7. Proposed GRU Based RNN Model Structure.

In this study, we utilize GRU, a type of RNN, to select the transmit MCS because the data is time series data. **Fig 7** shows the structure of GRU. The GRU algorithm is an RNN that is a modification of the Long Short-Term Memory (LSTM), which was conceived as a solution to the short-term memory problem of RNNs. Despite its simplicity, it is fast and has similar performance to LSTMs because it has fewer gates and parameters to train than LSTMs, so we use the GRU model in this study. The GRU is more suitable than the LSTM for this study because of its low complexity and short computation time due to the small number of parameters in the TDD communication system that quickly switches from receiving to transmitting. The proposed model is a many-to-one type regression model in which one received signal SNR is input in each cycle when training the model, and one value is output as the final output when all N data are cycled. The proposed RNN is organized into four GRU layers of 64, 32, 16, and 8 units, and the activation function uses hyperbolic tangent (Tanh). The following **Fig 8** shows the structure of the proposed RNN.

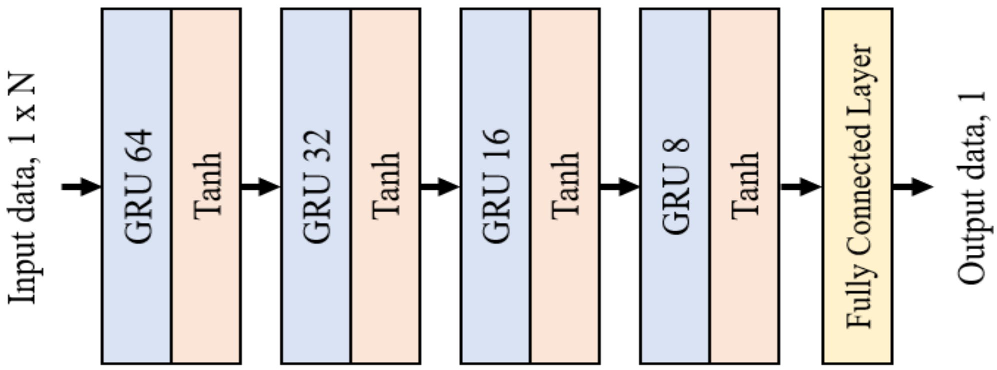

Fig 8. Proposed GRU based RNN Structure.

IV. SIMULATION AND RESULTS

Simulation Environments

For the computer simulations, we use MATLAB to generate data, leverage TensorFlow 2.0 to train and validate the GRU model and evaluate its performance.

Table 2. Simulation Parameters

Communication Parameters	Values	
	MCS Selection	
Number of Antenna, M	1	
Bandwidth	$2\ MHz$	
Carrier Frequency, f_c	$512\ MHz$	
OFDM System FFT Size	512	
Sampling Period, N_s	$6\ OFDM\ Symbol$	
Number of Received SNR, N	$N \in \{10,30,50,70,100\}$	
System SNR, SNR_s	$SNR_s \in [0,30]dB$	
Speed, v	$v \in [0,100]$km/h	
SNR Reception Failure Probability, p	$p \in [0.1,1]$	
Rician Factor, k	$10\ dB$	
LoS Probability	0.125	
Hyperparameters	**Values**	
	CNN	RNN
Optimizer	$AdaGrad$	$Adam$
Learning Rate	0.01	0.001
Batch Size	512	1024
Number of Epochs	500	100
Loss Function	MSE	

Table 2 shows the communication signal parameters of the simulation and the hyperparameters of the conventional CNN and the proposed GRU-based RNN. The number of antennas M used for receiving and transmitting is one. The bandwidth is $2\ MHz$, which is a broadband environment according to the military OFDM system, and the carrier frequency is assumed to be $512\ MHz$. The Fast Fourier Transform (FFT) size is 512, and the interval for sampling the received SNR is 6 OFDM symbols. The total number of timesteps of the received SNR to be used for selecting the MCS is experimented with 5 different numbers: $10, 30, 50, 70$, and 100, and the best length for each method is selected. For each training sample, the average SNR of the generated signal is randomly selected from 0 to 30 dB, and the traveling speed is randomly selected from a minimum of $0\frac{km}{h}$ to a maximum of $100\frac{km}{h}$. For each sample, the probability of signal reception at each timestep (the probability of the presence of the received SNR) is randomly selected from 10 to 100%. The channel model is randomly selected between Line of Sight (LoS) and Non-LoS, utilizing the Rayleigh (ITU Vehicular A) and Lycian channel models. The k-index of the Lycian channel is $10\ dB$. There is a 12.5% probability that a training sample is selected as a line-of-sight environment from the line-of-sight and non-LoS environments. For the conventional CNN model, the optimizer is AdaGrad, the learning rate is 0.01, the batch size is 512, and the epoch is 500, while the proposed RNN model has the optimizer Adam, the learning rate is 0.001, the batch size is 1024, and the epoch is 100. Both AIs use Mean Square Error (MSE) as the loss function. The training data is 200,000 and the validation data is 20,000. The MSE formula is shown in Equation 2 below.

$$1/n \sum_{i=1}^{n} (y_i - t_i)^2 \tag{2}$$

Simulation Results

To compare the performance of the proposed RNN with the existing methods, the average value method, the recent value method, the conventional CNN method, and the proposed RNN, we generate 20,000 test data each at 10 km/h intervals from 0 km/h to 100 km/h. For the length N of the received SNR to be used for prediction, CNN and RNN perform best when N=100, while for the average value, N=50 performs best. Compare the performance based on the optimal value of N for each method. The performance comparison metrics consist of three main indicators: SNR prediction Mean Absolute Error (MAE), the probability of outage resulting in communication interruption, and throughput. Performance variations of each method are observed across different speeds according to each performance comparison metric.

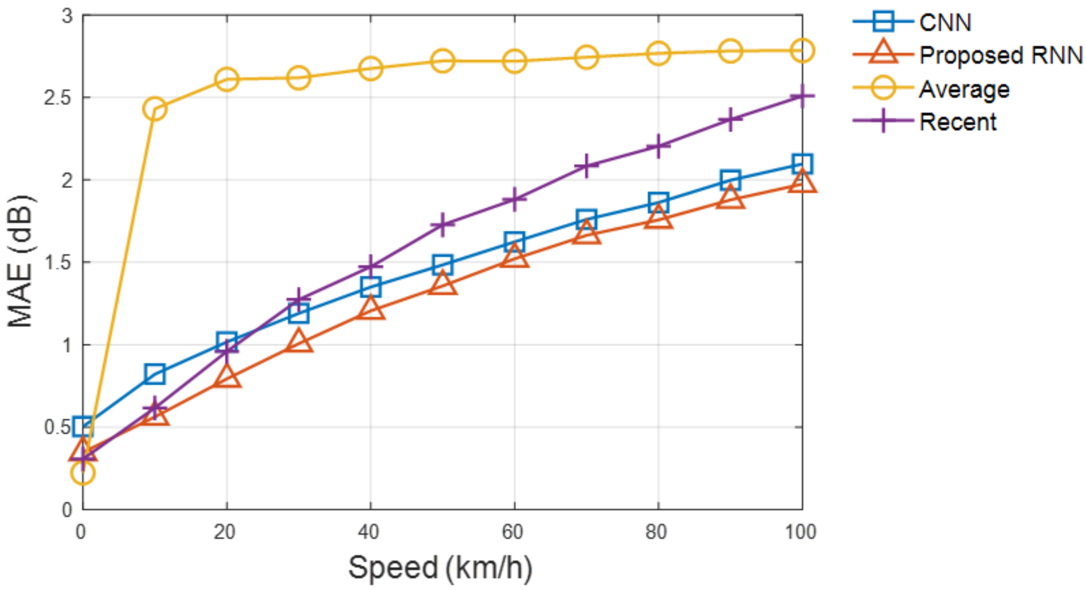

Fig 9. MAE for Speed.

Fig 9 shows the MAE of the SNR at the time of transmission estimated based on the received SNR. All methods show that the MAE tends to get worse as the speed increases. At speeds of 0 km/h, the average value method is the best. However, after 10 km/h, the average value method degrades rapidly and is the worst performing of all the methods. Compared to the conventional CNN, the recent values method has better MAE performance in the speed range below 20 km/h, but the conventional CNN outperforms it in the range above 30 km/h. The proposed RNN has the best performance in all speed bins above 10 km/h except 0 km/h. For all speed bins, the average value shows an average MAE of 2.461 dB, while the recent value is 1.582 dB, which is 0.879 dB better than the average value. For the conventional CNN, it is 1.428 dB, which is 0.154 dB better than the average value, and the proposed RNN is 1.279 dB, which is 0.149 dB better than the conventional CNN [16]. We can see that the proposed GRU-based RNN predicts the SNR with the smallest error.

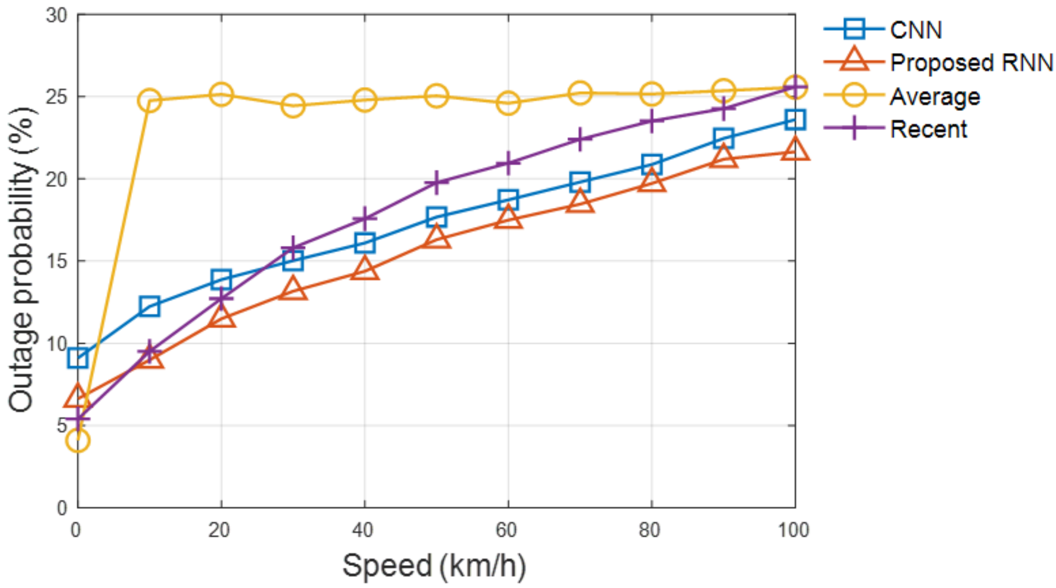

Fig 10. Outage Probability for Speed.

Fig 10 compares the probability of outage occurring with varying speeds when selecting MCS based on the estimated SNR. The outage probability graph exhibits a similar trend to the MAE graph for different speeds shown in **Fig 10**. This is because higher levels of MCS selection, based on predicted SNR with larger MAE, lead to a higher probability of communication interruption. The average value method shows the lowest probability of communication interruption at 0 km/h, but it exhibits the highest probability at speeds above 10 km/h. On the other hand, the recent value method demonstrates lower outage probability than the conventional CNN approach at speeds below 20 km/h, but it increases thereafter. It is evident that using AI methods for speeds above 30 km/h results in lower outage probability compared to conventional algorithmic approaches. The proposed RNN shows a slightly higher outage probability of 1.5% to 3% compared to the existing average value or recent value methods at 0 km/h. However, in all speed ranges except for 0 km/h, the proposed RNN exhibits the lowest outage probability. At a speed of 10 km/h, the proposed RNN shows a 15.555% lower outage probability than the average value method and a 0.4% lower outage probability than the recent value method. The proposed RNN demonstrates an average outage probability of 15.404%, which is 7.617% better than the average value method. This indicates that the proposed RNN ensures the highest communication stability.

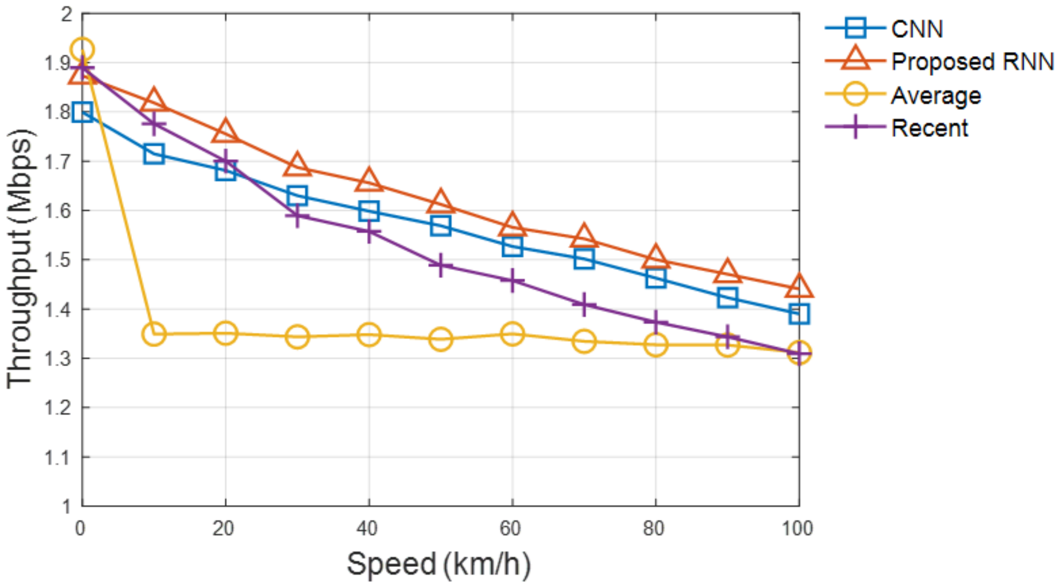

Fig 11. Throughput for Speed.

Fig 11 illustrates the throughput based on the estimated SNR when selecting MCS according to speed. When outage occurs, the throughput is calculated as 0 bps. Overall, it is observed that as the speed increases, the achievable throughput decrease for all methods. This phenomenon occurs because as the speed increases, the channel conditions deteriorate due to factors such as Doppler effects, leading to a decrease in the highest level of MCS that can be selected without encountering outage. At 0 km/h, the average value method exhibits the highest performance, followed by the recent value method, the proposed RNN, and the conventional CNN method in descending order of transmission speed. However, in the speed range of 10 km/h to 20 km/h, the average value method shows the worst performance, with the proposed RNN, the recent value method, and the conventional CNN method exhibiting superior performance. In the speed range above 30 km/h, both artificial intelligence methods outperform the recent value and average value methods, with the proposed RNN demonstrating more than 50 kbps better performance than CNN. As evidenced by the MAE graph in **Fig 9**, performing accurate SNR predictions enables higher throughput. When SNR prediction exceeds the actual SNR, it leads to the selection of a higher level of MCS than what is feasible, resulting in communication outage. Since communication outage renders transmission impossible, it results in significant losses in terms of transmission speed. The proposed RNN demonstrates higher throughput than all other methods in all mobile situations, except for stationary situations at 0 km/h, where Doppler effects are present.

V. CONCLUSION

In this paper, we propose a system to select the optimal MCS using GRU-based RNN for one-to-one tactical vehicle-to-vehicle communication. The proposed method uses the SNR of the received signal as an input to the artificial intelligence model to predict the SNR at the time of transmission and select the MCS. Unlike previous studies that utilize CNNs, which have shown the best performance, we utilize GRUs, a type of RNN, to utilize time series data. The proposed RNN has an average SNR prediction MAE of 0.149 dB better than the existing CNN. Based on this, we selected MCS, and the probability of communication loss is 1.818% lower on average than that of conventional CNN, which shows better performance, and the transmission rate is 56.8 $kbps$ faster on average. The proposed GRU-based RNN demonstrated superior performance compared to both conventional AI methods and algorithmic approaches in mobile scenarios.

Through this study, it is expected that higher communication stability and higher transmission speed can be guaranteed in tactical OFDM environments, which will provide a more favorable communication system for tactical communication. Especially in tactical communication environments, where extreme communication scenarios with intermittent reception must be considered, ensuring uninterrupted communication is crucial. Therefore, this study is significant. As a future research plan, we intend to develop a system model that utilizes multiple antennas for reception and selects the optimal antenna for transmission simultaneously with the optimal MCS selection.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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