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Prediction of Signal to Noise Ratio Based on Deep Learning in Tactical Wireless Communication Systems

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Abstract

In this paper, we propose a prediction technique for future signal to noise ratio based on deep learning in tactical wireless communication systems. The communication system considered in this paper receives with multiple antennas and transmits in the future using the same antenna. We propose a deep learning model that predicts SNR for each transmit antenna in future transmission situations based on SNR received from multiple receive antennas in the past. Received ratio or a recorded ratio of a received SNR is set to 10 to 100 %. If there is no received record nor SNR record, the received SNR is set through linear interpolation of the previously received SNR and the subsequent received SNR. According to the simulation results, wideband signals (4MHz) show better predictive performance than the narrowband signals (25kHz). In case of wideband, the proposed method is about 0.37 dB to 0.98 dB superior to the conventional method when the moving speed is over 20 km/h. For narrowband signals, the proposed method is about 0.29 dB to 0.88 dB better than the conventional method for the moving speed over 20 km/h. Those result indicates that the proposed prediction technique can be applied to antenna selection problem that provides the best SNR.

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1. Introduction

Tactical wireless communication system is popular nowadays to transmit large amounts of voice, data, and video while moving fast (Mourougayane, K. et al., 2020, Riihonen, T. et al., 2018, Zou, X. et al., 2020). In the mobile wireless communication environments, reliable communication is difficult because the line of sight is rarely guaranteed (Wang, H. et al., 2019). The channel environment is similar to the general multipath fading channels (Matolak, D.W. et al., 2011), and a problem occurs in that the quality of the signal changes time to time (Lima Filho, V.C. et al., 2021). Rapid SNR change can severely degrade communication reliability (Sun, W. et al., 2020). To solve this problem, there is a method using multiple antennas (Ahn, S.J. et al., 2021). Although the method of receiving using multiple antennas in a mobile environment is a promising technique, transmitting using all of the multiple antennas is not. The signals from multiple antennas may interfere with each other, resulting in a multipath fading effect. Therefore, it is important to select one optimum antenna and transmit, rather than using all the multiple antennas (Gao, Y. et al., 2017).

In this paper, we propose a technique for predicting the signal to noise ratio (SNR) of the future at the time of transmission for each antenna in an environment where multiple patchy directional antennas are attached to the communication vehicle to communicate with the other party. Through this, it is possible to select and transmit an antenna having the best SNR. Although the directional antenna can transmit and receive in only one direction, it has a high gain and a high effect in preventing interference (George, R. et al., 2020). The proposed method predicts the SNR at the transmission time for each antenna in the future using convolutional neural network (CNN) based on the past received SNR information for each antenna in a mobile wireless communication environment (Jeong, E.R. et al., 2020). In this paper, we presume a TDD method in which transmitting and receiving antennas share time separately at the same frequency (Jose, J. et al., 2011). Since the receiving SNR may be recorded only when received, performance according to the receiving ratio is important. Therefore, in this paper, the reception ratio or the reception SNR recording ratio is varied from 10 to 100 %. If there is no received record and there is no SNR record, the received SNR is established through linear interpolation of the previously received SNR and the subsequent received SNR.

The performance of existing and proposed techniques is verified through computer simulation and evaluated according to the speed of the communication vehicle. The performance indicator uses the Mean Absolute Error (MAE) between the actual SNR and the predicted SNR. As a result of simulation, wideband performance is better than narrowband. For wideband, the proposed method is superior to about 0.37 dB to 0.98 dB based on speed of above 20 km/h. For narrowband, the proposed method is superior to about 0.29 dB to 0.88 dB based on speed above 20 km/h.

This paper is organized as follows. Section 2 describes the overall system model. In section 3, SNR prediction methods for conventional and proposed methods are introduced. Section 4 compares the performance of the proposed method and the conventional method. Finally, section 5 concludes the paper.

2. System Model

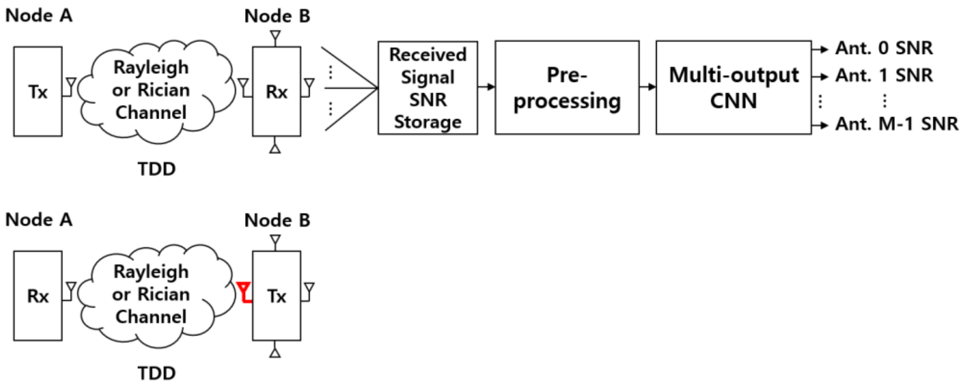

Fig. 1; Communication System Mode

The communication system considered in this paper is as follows. The node receives and transmits using multiple directional antennas attached to a communication vehicle. When receiving, all antennas are used for data reception and store the received SNR at that time. When transmitting, only one antenna is selected among all the antennas and transmits using the antenna. Transmission and reception are performed with the same frequency but different time, i.e., time division duplexing (TDD) technique. Therefore, the optimal antenna sould be selected for transmission to increase the communication data rate or reliability. To this end, the system proposed in this paper predicts the SNR of each antenna at future transmission time based on the SNR information received in the past. Figure 1 shows a system model for predicting the SNR of the future transmission antenna. The detailed scenario is as follows. In figure 1, Node A transmits signal to Node B through Rayleigh Channel or Rician Channel. In Node B, the SNRs of all the received antennas are calculated and stored from the received antennas. Based on the SNRs received from multiple antennas, we predict the future SNRs through artificial intelligence (AI) and select the optimal transmission antenna.

Hereafter, we explain the preprocessing for the AI input. In preprocessing, the received SNRs recorded previously is vectorized, and the received SNR vectors for each antenna are combined to generate a received SNR matrix. First, the SNR simultaneously received at multiple antennas are expressed as follows.

$$\mathrm{x_n} = [\mathrm{x_{0,n}}, \mathrm{x_{1,n}}, \dots, \mathrm{x_{M-1,n}}]^{\mathrm{T}} \quad (1)$$

where $\mathbf{x}_{\mathrm{n}}$ is a received SNR vector, n is a time index of a received packet, and M is the total number of antennas. After combining the SNR vectors from all the antennas, the received SNR matrix is given by

$$\mathbf{X_N} = \begin{bmatrix} \mathrm{x_{0,0}} & \mathrm{x_{0,1}} & \cdots & \mathrm{x_{0,N-1}} \\ \mathrm{x_{1,0}} & \mathrm{x_{1,1}} & \cdots & \mathrm{x_{1,N-1}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{x_{M-1,0}} & \mathrm{x_{M-1,1}} & \cdots & \mathrm{x_{M-1,N-1}} \end{bmatrix} \quad (2)$$

where $\mathrm{X_N}$ is a past received SNR matrix of size $\mathrm{M} \times \mathrm{N}$ for predicting SNR at the future transmission time (or time index) N. Each row represents an SNR received from an antenna, and each column represents SNR of all antennas obtained at a specific reception time, n. Therefore, the size of the SNR matrix X_N depends on the number of operating antennas and the length of the past received SNR observation time.

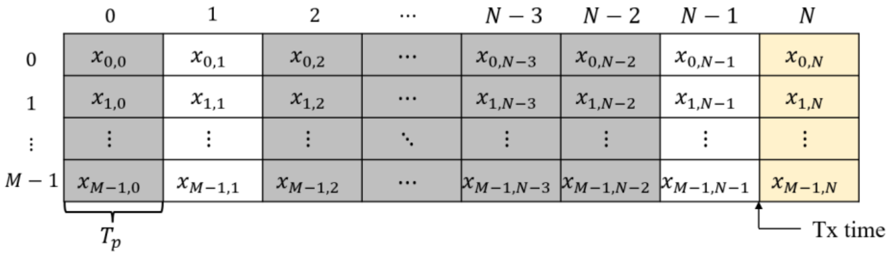

Fig. 2; Example of Received SNR Matrix

Figure 2 shows example of the received SNR matrix. Bearing in mind that the transmit and receive antennas communicate at different time but the same frequency, received SNR does not exist in some time indexes. In Figure 2, the dark areas $\mathbf{x}_0$, $\mathbf{x}_{N-3}$, $\mathbf{x}_{N-2}$, etc. indicate that the packet is received and the SNR is recorded, and the bright areas indicate that the SNR could not be recorded because there was no received packet. In Figure 2, $\mathbf{x}_1$, $\mathbf{x}_{N-1}$ is the case where the packet is not received. Under this realistic scenario, the problem is to predict the SNR of each antenna ($\mathbf{x}_N$) when transmitting at the future time index N.

Assuming that the symbol rate of the communication signal is R_s and the number of symbols in one packet is N_s, the symbol period and the packet length are expressed as (3) and (4), respectively.

$$T_s = \frac{1}{R_s} \qquad (3)$$

$$T_P = T_s \times N_s \quad (4)$$

This paper consider two types of signals: wideband and narrowband signals. The wideband signal has a small packet length T_p because the symbol rate is relatively high compared to the narrowband signal. T_p is determined by the bandwidth of the signal and has an inversely proportional to the bandwidth. Assuming that the number of symbols in packet is the same regardless of signal bandwidth, the narrowband signal requires longer time to construct the SNR matrix in Figure 2.

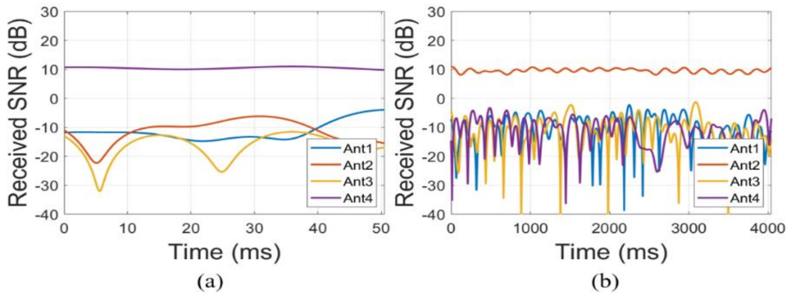

Fig. 3; Received SNR over Time in Rician Channel (a) Wideband Signal (b) Narrowband Signal

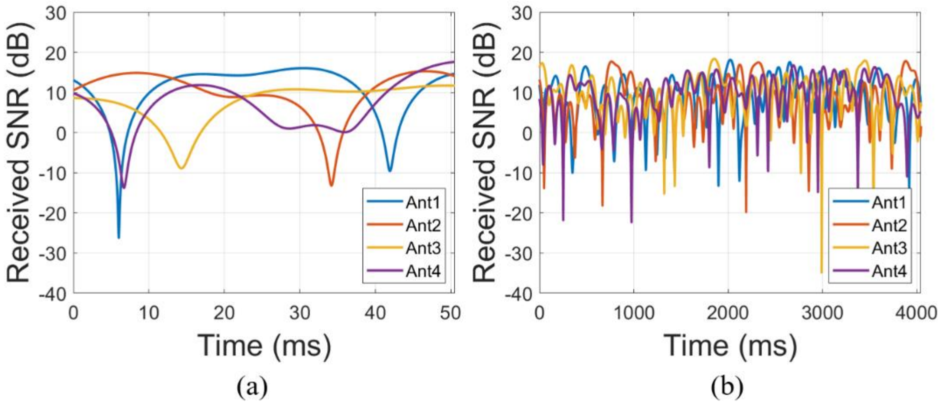

Fig. 4; Received SNR over Time in Rayleigh Channel (a) Wideband Signal (b) Narrowband Signal

Figure 3 and 4 show the SNR of the received signal over time in Rician Fading and Rayleigh Fading channels, respectively. Figure 3(a) and 4(a) show the SNRs for the wideband signal, and Figure 3(b) and 4(b) show the SNRs for the narrowband signal. In the figure, the x-axis is time and the y-axis is the received SNR at each antenna. The Rician fading channel has the line of sight so that the direct wave and reflected waves exist simultaneously. The Rayleigh fading channel does not have line of sight so that the received signal is composed of only reflected waves. As shown in Figure 3 and 4, the wideband signal has a relatively short SNR measurement period compared to the narrowband signal. It is observed that the channel change speed of the wideband signal is slow over time, while the channel of the narrowband signal is rapidly changing.

3. Proposed SNR Prediction Method

The proposed method is to predict $\mathrm{x_n}$, which is the SNR for each antenna at a transmission time N from the received SNR matrix $\mathrm{X_N}$. The conventional technique is configured as follows. This method is first measuring the SNR of the most recently received packet and predict it (or use it) for the SNR at the future transmission time N. This method is a natural method when the channel is time-varying.

In contrast, the proposed method utilizes all the SNR records in the past, and the received SNR matrix is used. In the proposed technique, when a packet is not received at certain time, the received SNR is filled through linear interpolation of the previously received SNR and the subsequently received SNR. In addition, if there is no SNR received at the start time (n = 0) of the SNR matrix or at the end time (n = N-1) of the SNR matrix, the received SNR is set to 0 dB. The received SNR matrix through this preprocessing becomes the input of the proposed CNN predictor.

Conventional SNR Prediction Method

The conventional method predicts the SNR at the time of future transmission by measuring the SNR with the most recently received packet information among time window N of the received SNR matrix. For example, since the most recently received packet in the received SNR matrix in Figure 2 is $\mathrm{x_{N-2}}$, the SNR for each antenna at the time of transmission is predicted as $\mathrm{x_N} =$

x_{N-2}.

Proposed CNN-based SNR Prediction Method

In the proposed method, when the received SNR cannot be measured because there is no received packet, the received SNR is set through linear interpolation of the previously received SNR and the subsequently received SNR. Linear interpolation is performed as follows. It is assumed that SNR is recorded first at the k-th time and then at the l-th time, but SNR is not recorded between them. To perform linear interpolation, first, the amount of change (Δ_n) of adjacent packet is calculated using the SNR of the received packet. the formula to find Δ_n is as follows.

$$\Delta_n = (x_l - x_k)/(l - k), \qquad (l > k) \quad (5)$$

where $\mathbf{x}_l$ and $\mathbf{x}_k$ represent the l-th and k-th received SNR vectors. Assuming that the index that did not receive the packet is p, the range of p is represented by $k < p < l$ and linear interpolation is performed as

$$x_p = x_{p-1} + \Delta_n, \qquad (p = k + 1, k + 2, \cdots, l - 1) \quad (6)$$

The received SNR matrix generated by the above process becomes the input of the proposed CNN predictor.

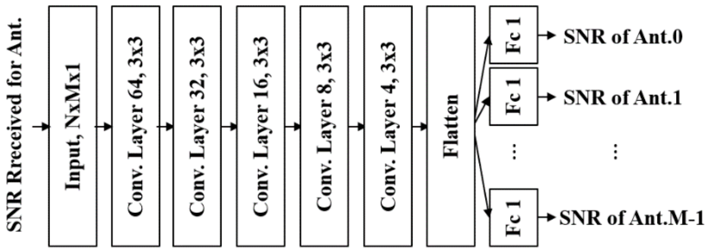

Fig. 5; Proposed CNN Model Structure

Figure 5 shows the proposed CNN model for the future SNR prediction. The input is the received SNR matrix obtained from multiple antennas and the output is the future SNR prediction value for each antenna. It consists of a total of 5 convolutional layers and M fully connected layers, and the size of the filter is 3x3 for all the convolutional layers. The depth of the filter consists of 64, 32, 16, 8, and 4, and after each convolutional layer, batch normalization layer and activation function are followed. The activation function is ReLU. Flatten is performed to transform the features extracted from the last convolutional layer into one-dimensional vector, and each antenna is connected with fully connected layer. Both narrowband and wideband use the same CNN model.

4. Simulation Results

4.1.Simulation Environment

Training and testing of the proposed CNN are performed using Tensorflow 2.0, and MATLAB is used for input data preprocessing. Table 1 shows the parameters of the simulation environment. In case of wideband, the bandwidth is 2 MHz, the symbol period is 0.5 ms, and the carrier frequency is 512 MHz. In the case of narrow band, the bandwidth is 25 kHz, the symbol period is 40 ms, and the carrier frequency is 88 MHz. The SNR is randomly generated with a value between 0 dB and 30 dB. The K-factor, power ratio of direct and reflected waves in the Rican channel, is 14 dB. The number of antennas (M) is 4, and the number of packets (N) is 100. The number of symbols per packet (N_s) is set to 1,000. The probability of reception (or recording) is 10 to 100%.

Table 1. Parameters for simulation

Parameter	Value
BW	2 MHz / 25 kHz
Symbol Period (T_s)	0.5 ms / 40 ms
Carrier Frequency	512 MHz / 88 MHz
Average SNR	0~30 dB
K-factor	14 dB
Num. of Antenna (M)	4
Num. of Packet (N)	100
1 Packet (N_s)	1,000 symbols
Packet Ratio	10 ~ 100 %

4.2.Training CNN

For the training data, 80,000 data set is generated randomly in the speed range from 0 to 100 km/h, and the 20,000 test data is generated at 10 km/h intervals from 0 to 100 km/h to examine the prediction performance by speed. The size of X_N is set to 4×100. That is, the artificial neural network input signal corresponds to the length of 100 packets. The parameters used for training are batch size 512 and epoch 2,000. Optimizer is Adagrad, and learning rate is 0.01. The loss function is mean square error (MSE)

$$\mathrm{MSE} = \frac{1}{D_{train}} \sum_{i=1}^{D_{train}} \left(\mathbf{x}_{N,i} - \hat{\mathbf{x}}_{N,i}\right)^2 \quad (6)$$

$x_{N,i}$ is x_N in the i-th learning data, $\hat{x}_{N,i}$ represents the predicted value of the i-th training data, and D_{train} represents the total number of learning data. The difference between the x_N and the predicted value $\hat{x}_N$ is squared and summed, and then divided by the total number of training data.

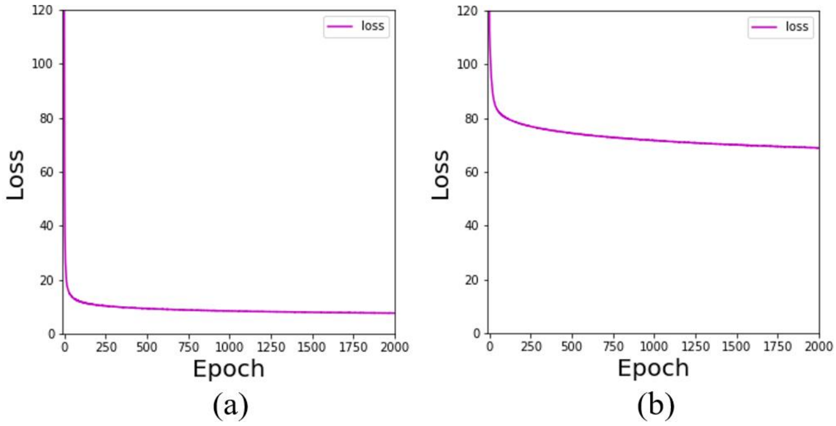

Fig. 6; Learning Curves (a) Wideband (b) Narrowband

Figure 6 is a learning for the loss. Figure 6 (a) is the learning curve for the wideband, and Figure 6 (b) is the learning curve for the narrowband. The x-axis is epoch and the y-axis is loss. The loss converges to about 7 for wideband and to about 68 for narrowband.

4.3.Test Results

Figure 7 shows MAE performance according to speed. Figure 7(a) is the MAE performance for wideband, and 7(b) is the MAE performance for the narrowband. Equation (7) is the MAE equation, which is a performance indicator for the test.

$$\mathrm{MAE} = \frac{1}{\mathrm{D_{test}}} \sum_{\mathrm{i}=1}^{\mathrm{D_{test}}} \left| \mathrm{x_{N,i}} - \hat{\mathrm{x}}_{\mathrm{N,i}} \right| \quad (7)$$

Where $\mathrm{x_{N,i}}$ is $\mathrm{x_N}$ in the i-th learning data, $\hat{\mathrm{x}}_{\mathrm{N,i}}$ represents the predicted value of the i-th test data, and $\mathrm{D_{test}}$ represents the total number of test data. The difference between the $\mathrm{x_N}$ and the predicted value $\hat{\mathrm{x}}_{\mathrm{N}}$ is obtained, and the absolute value is summed up and divide it by the total number of test data.

In Figure 7, the red dotted line and regular triangle (△) marker are the case of the proposed method, and the blue solid line and square (ϒ) marker are the case of the conventional method. In the wideband, the MAE of the proposed method increases from 0.29 dB to 0.98 dB in the speed range of 0 to 100 km/h, and the conventional method increases from about 0.01 dB to 1.41 dB. In the narrowband case, the MAE of the proposed method increases from about 1.38 dB to 3.78 dB in the speed range of 0 to 100 km/h, and the conventional method increases from about 0.14 dB to 4.66 dB. In the case of wideband, the MAE is about 0.37 dB to 0.98 dB at speed of above 20 km/h, and the proposed method is about 0.01 dB to 0.44 dB superior to the conventional method. In the case of narrowband, the MAE is about 2.47 dB to 3.78 dB at speed of above 20 km/h, and the proposed method is about 0.29 dB to 0.88 dB superior to the conventional method. Those results indicate that for slow moving speed, the conventional method is better than the proposed method. However, if the moving speed is over 20 km/h, the proposed method is superior to the conventional method, and the performance gap increases as the speed increases.

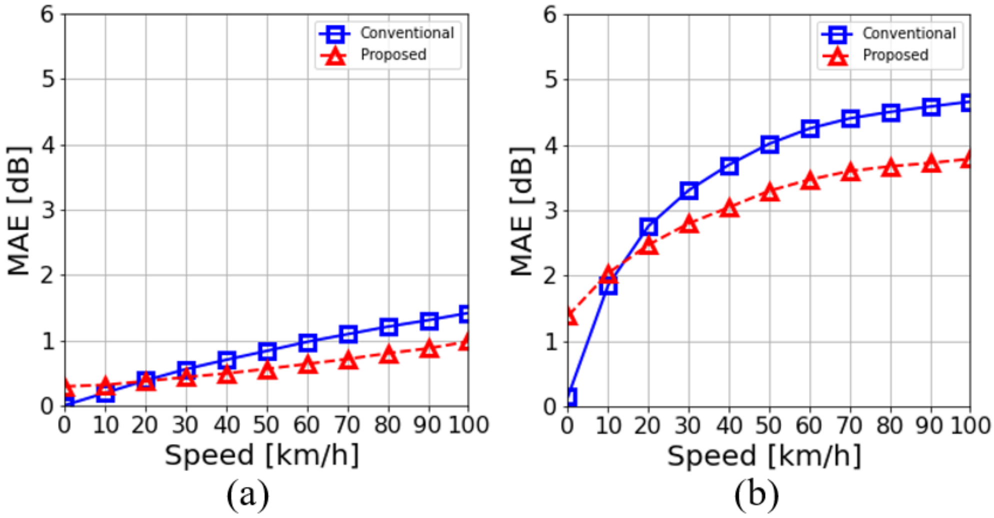

Fig. 7; Result of SNR Prediction on Speed

5. Conclusion

This paper proposed artificial intelligence method that predicts future SNR using receiving SNR of multiple antennas in tactical wireless communication environment.

The input signal, or the received SNR, is mixture of Rician fading channel and Rayleigh fading channel. For slow moving speed, the conventional method is better than the proposed method. However, if the moving speed is over 20 km/h, the proposed method is superior to the conventional method, and the performance gap increases as the speed increases. If the proposed method is applied to an actual communication system, it will be possible to transmit at the highest transmission rate while increasing the communication success probability by using the optimal transmit antenna.

References

1. Ahn, S.J. Lee, J.Y. Lim, B.M. Kwon, H.C. Hur, N. & Park, S.I. (2021). Multi-antenna diversity gain in terrestrial broadcasting receivers on vehicles: A coverage probability perspective. ETRI Journal, 43, 400-413. https://doi.org/10.4218/etrij.2020-0242
2. Gao, Y. Vinck, H. & Kaiser, T. (2017). Massive MIMO antenna selection: Switching architectures, capacity bounds, and optimal antenna selection algorithms. IEEE Transactions on signal processing, 66, 1346-1360. DOI: 10.1109/TSP.2017.2786220
3. George, R. & Mary, T.A.J. (2020). Review on directional antenna for wireless sensor network applications. IET Communications, 14, 715-722. https://doi.org/10.1049/iet-com.2019.0859
4. Jeong, E.R. Lee, E.S. Joung, J. & Oh, H. (2020). Convolutional neural network (CNN)-based frame synchronization method. Applied Sciences, 10, 7267. https://doi.org/10.3390/app10207267

5. Jose, J. Ashikhmin, A. Marzetta, T.L. & Vishwanath, S. (2011). Pilot contamination and precoding in multi-cell TDD systems. IEEE Transactions on Wireless Communications, 10, 2640-2651.
   DOI: 0.1109/TWC.2011.060711.101155
6. Lima Filho, V.C. & Moraes, A. (2021). Modeling multifrequency GPS multipath fading in land vehicle environments. Gps Solutions, 25, 1-14. DOI: https://doi.org/10.1007/s10291-020-01040-8
7. Matolak, D. W. & Frolik, J. (2011). Worse-than-Rayleigh fading: Experimental results and theoretical models. IEEE Communications Magazine, 49, 140-146. DOI: 10.1109/MCOM.2011.5741158
8. Mourougayane, K. & Srikanth, S. (2020). A tri-band full-duplex cognitive radio transceiver for tactical communications. IEEE Communications Magazine, 58, 61-65. DOI: 10.1109/MCOM.001.1900329
9. Pärlin, K. Riihonen, T. Le Nir, V. Bowyer, M. Ranstrom, T. Axell, E. Asp, B. Ulman, R. Tschauner, M. & Adrat, M. (2021). Full-duplex tactical information and electronic warfare systems. IEEE Communications Magazine, 59, 73-79. DOI:10.1109/MCOM.001.2001139
10. Sun, W. Yu, H. Yang, Y. Li, Q. Mu, D. & Xu, X. (2020). Confidence interval based model predictive control of transmit power with reliability constraint. Wireless Networks, 26, 3245-3256.
    https://doi.org/10.1007/s11276-019-02202-4
11. Wang, H. Zhang, P. Li, J. & You, X. (2019). Radio propagation and wireless coverage of LSAA-based 5G millimeter-wave mobile communication systems. China Communications, 16, 1-18.
    DOI: 10.23919/j.cc.2019.05.001
12. Zou, X. Yang, R. Yin, C. Nie, Z. & Wang, H. (2020). Deploying tactical communication node vehicles with Alpha Zero algorithm. IET Communications, 14, 1392-1396. https://doi.org/10.1049/iet-com.2019.0349