VOL. 18, NO. 14, JULY 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

NEURAL NETWORK-BASED RECEIVER DIVERSITY COMBINATION FOR HIGH-FADNG CHANNELS

J. Raja Chidambaram, Barath Balaji, Saravanan K. and Bagubali A.
School of Electronics Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India
E-Mail: rajachidambaram.j2019@vitstudent.ac.in

ABSTRACT

In today's modern world, many improvements and developments in Wireless Networks have brought changes in the convenience of people's life. In this paper, we are proposing a new method on the topic of receiver diversity combining. Selection diversity, maximal ratio combining, equal gain combining, and switched diversity are existing methods for space diversity techniques. We have used various neural network models to predict the received message based on the received signals in multi-receiver environments, therefore, proposing a new method for space diversity combination. Comparisons with the existing methods are done in Python through simulations.

Keywords: receiver, neural network, MRC, BER, SNR, Python.

Manuscript Received 28 April 2023; Revised 17 September 2023; Published 30 September 2023

INTRODUCTION

In order to improve the system performance in the case of significant fading, different methods are used, but diversity combining techniques are most frequently applied. Diversity techniques are applied to improve the reliability of the system by creating two or more channels. When we transmit the signal through multiple channels, we will receive multiple versions from the various receivers. Diversity combining is the technique applied to combine the multiple received signals of a diversity reception device into a single improved signal [1]. Then the signal can be equalized and demodulated. There are two types of diversity techniques based on the type of fading. They are small-scale diversity techniques where the transmitter and receiver are close by, usually a meter apart. The other one is the large-scale diversity technique where the antennas are quite apart and are not shadowed. The aim of the project is the improve the quality of the receiver diversity combination. With the existing methods, we can obtain great efficiencies and low bit error rates. But, with the latest technologies like massive MIMO (Multiple Input Multiple Output) [2], EMBB (Enhanced Mobile Broadband), and URLLC (Ultra-reliable Low Latency Communication) we can go a step further and see if we can reduce the Bit error rate by using a new receiver combination technique. In this paper, we have tried to use neural networks to try and reduce the bit error rate.

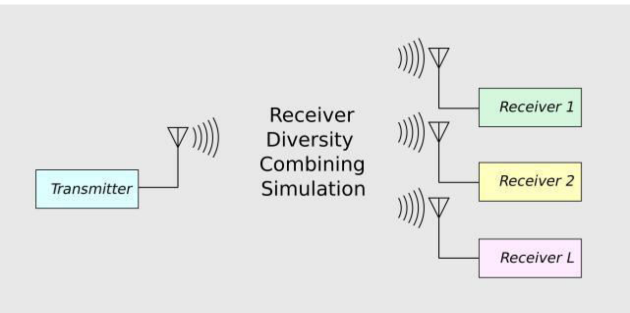

Figure-1. Diversity combining.

EXISTING METHODS

Selection Combination

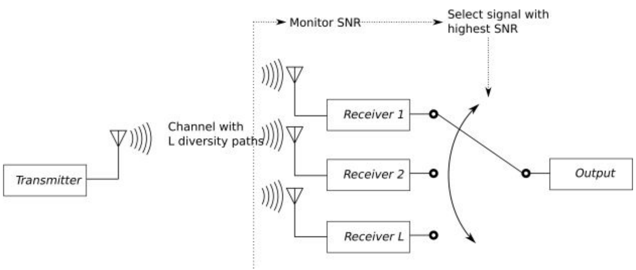

Figure-2. Selection combining.

Selection combining is the simplest method for combining signals in a diversity system, which is based on choosing the branch with the most favourable Signal-to-noise Ratio.[3] Selection combining receiver estimates the current value of SNR in all branches and selects the one with the most favourable SNR. Then the signal is sent for demodulation.

Maximal Ratio Combining

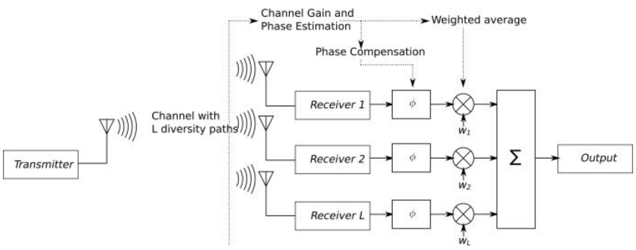

Figure-3. Maximal ratio combining.

Maximal Ratio Combining is the optimal linear technique of received signal combination in the multi-path system, which provides the best statistical results in

ARPN Journal of Engineering and Applied Sciences

limiting the impact of fading and noise. The signals in each of the branches are multiplied by the weighting factors before being summed, and the branches with a more favourable signal-to-noise ratio is taken with a greater contribution. The weighting factor keepson changing dynamically. This ensures that the signal with more power has a greater contribution to the received sum of signals. Therefore, it is necessary to have a measurement of SNR in all branches, and that is why this technique is expensive for practical implementation. [4] Even though it has acomplex heavy circuit design, it provides the best Bit-error-rate among the existing methods. [5]

Equal Gain Combining

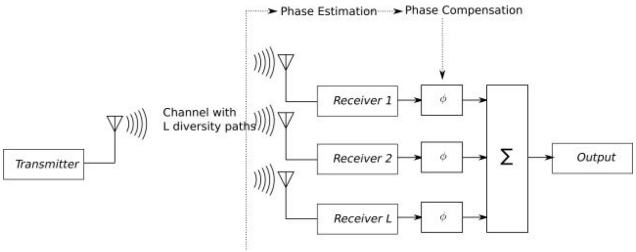

Figure-4. Equal gain combining.

When we use the Equal Gain Combining technique in the receiver branches, phase alterations of signals in all diversity branches are neutralized, and then signals are added. Unlike the MRC technique, all branches have the same weighting factor, so it is not required to measure and estimate Signal-to-Noise Ratio in all diversity branches. [6] That's why this technique is simpler and cheaper for practical implementation. It gives slightly worse performance compared to MRC technique. [7].

Switched Diversity

Switched Diversity is a basic method for combining signals in a Diversity system based on randomly choosing the branch. If there are 4 paths, the receiver will directly pick a random one and will estimate the signal sent. Systems that use Switched Diversity can provide good gains but only whenthe switching threshold is not very big or very small compared to the average signal-to-noise ratio. [8]

NEURAL NETWORK METHOD

We generated a dataset using various libraries consisting of channel data and received signals with noise with real and complex values. Using this dataset, we train the model using Neural Network. While coming across various Neural Network models for our project, we have tried to use Artificial Neural Network (ANN)[9] and Binarized Neural Network(BNN) [10][11] in our project. Using the Keras Sequential model, which is a linear stack of layers, we created a model by passing the list of layer {2n,n,1} in to the constructor, and we predict the output. Here in denotes the number of branches.

For example, if we take four branches. Therefore, in the first sequence, the layer has twice the number of branches that is 8 neurons. In the second sequence, the layer has the same number of neurons as the number of branches, and in the final layer, it contains only one neuron and technically it is called as the Binary Neuron.

Along with the neural layer, we have used two activation functions [12]: tanh and ReLU. This activation function is mainly used to get the output of the node. The output may be in the form of 'yes' or 'no' mapping the values between -1 to +1 depending upon the function.

The Tanh or Hyperbolic Tangent Activation Function ranges from -1 to +1. This function is sigmoidal (s-shaped). Its function is differentiable, indicating that the slope of the sigmoid curve at any two points can be identified. Tanh function is monotonic, whereas its derivative is non-monotonic. We have used it only the last binary neuron as we need the network to predict 1s and -1s.

$$f(x) = \tanh(x) = \left(\frac{2}{1+e^{-2x}}\right) - 1$$

ReLU is a non-linear activation function that gives the out- put similar to its input if it is positive, otherwise it gives 0. This function is used in almost all Neural Network and Deep Learning models. In ReLU, both the function and its derivative are monotonic. ReLU is widely used for its simpler computation where the derivative remains constant and the time taken for the model is minimized along with the errors. Another advantage of ReLU is its capability of outputting a true zero value. We have used this function in all the other neurons that build up towards the final binary neuron.

$$f(x) = \max(0, x)$$

This model is trained for almost 10 epochs. In each epoch, the accuracy and loss of the model is analysed and tested. This model is then saved in a .h5 file. Then we load the model in the main code. Once the Neural Network model is loaded in the main code, we feed the real time channel parameters into the neural network to predict the received signal. With the help of this actual received signal, we calculate the bit error rate for all the predicting methods and compare the performances. If each neuron is a binarized neuron then the power consumption is reduced by 32 times the GPU, improving the power efficiency and reduce the memory size.

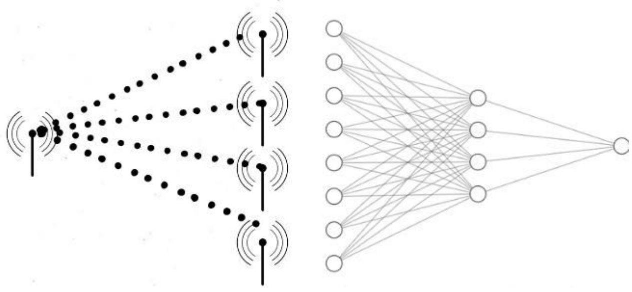

Figure-5. Neural network at the receiver.

ARPN Journal of Engineering and Applied Sciences

ALGORITHM

In this project, we have used three sets of codes on the Jupyter notebook editor. The first code is to generate data for training, the second code is to design and train the neural network and the final code is the main code, where we compare the performance of the neural networks with the other existing methods. We have used the BPSK as the digital modulation scheme as used in [7].

Algorithm for main code

1	**Import packages like Random, Matplotlib and Keras**
2	Declare variables – No of diversity branches, No of simulations, SNR Range
3	for Number of simulations do
4	for SNR Range do
5	Generate BPSK Symbol
6	Generate Fading vectors
7	Generate Noise
8	Generate channel
9	Calculate BER for each for the 5 methods
10	End for
11	End for
12	We plot the graph comparing the BER across various SNR values

Noise is generated using the below formula. The channel is generated and the noise is also randomized. Then we generate the fading vector using the formula below.

$$Y = (H * X) + W$$

where H is the channel, X is the transmitted BPSK signal and W is the noise vector.

$$\text{Noise} = 10^{-\text{SNR}/10}$$

Under 9th point from the above steps. The process of calculation for each method is given below. We calculate BER foreach of the 5 methods in each simulation and sum it up using this formula.

$$BER_x = BER_x + \frac{F}{Nsim}$$

where Nsim is the number of simulations, and F is the flag that denotes 1 when the receiver signal matches the transmit-ted signal and 0 otherwise.

a. Selection Diversity

Find the absolute value of all the channel vectors. Pick the channel branch with the maximum absolute value. Find the conjugate of that particular channel. Multiply it by the signal with fading vector. Take only the real part, if its lesser than 1, then received signal is -1, else its 1. BER is calculated at each step.

b. Maximal Ratio Combination

Find the conjugate of all the channel vectors. Multiple each by its own faded vector. Add all the branches. Take only the real part, if its lesser than 1, then received signal is -1, else it is 1. BER is calculated at each step.

c. Switched Diversity

Pick a channel vector by random. Multiply it by its own faded vector. Take only the real part, if its lesser than 0, then received signal is -1, else its 1. BER is calculated at each step.

d. Equal Gain Combining

Find the angle of all the channel vectors. Multiply it with the faded signal. Raise the answer to the exponent of e. Sumall the exponents. Take only the real part, if it's less than 0,then the received signal is -1, else it is 1. BER is calculated at each step.

e. Neural Network

Import the .h5 file which contains the built neural network. Run the channel and faded signal values through the neural network and obtain an output. Take only the real part, if it is less than 0, then the received signal is -1, else its 1. BER is calculated at each step.

SIMULATION

When we plot the graph to find the efficiency of the receiver, we have SNR values on the x-axis and the BER on the y-axis. Traditionally as the SNR increases the Bit error rate decreases. [15] They are almost inversely proportional. Initially, the line is flat and around the value of SNR = 0, the line slopes downwards and after a certain value of positive SNR, the line flattens again. [14] When we ran the simulations, it was found that since the neural network only learns from the data it is put through when trained, our method performs better on the wider ranges. In the first set of simulations, the methods are compared for only 2 branches. There are three plots. The first plot is for the SNR range of -15 to -5. The second plot is for the SNR range of -5 to 5, and the last plot is for the SNR range of 5 to 15.

VOL. 18, NO. 14, JULY 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

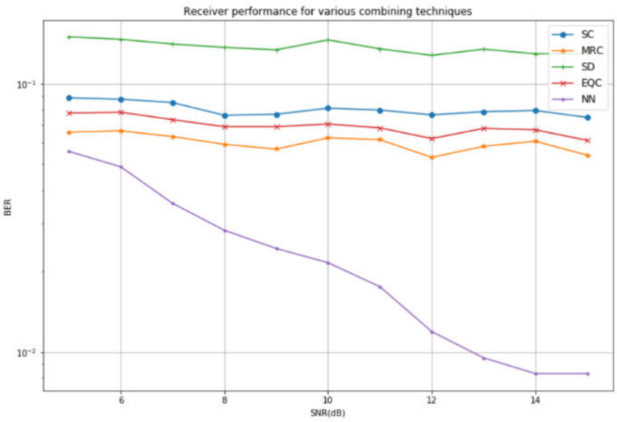

Figure-6. Medium SNR for 2 branches.

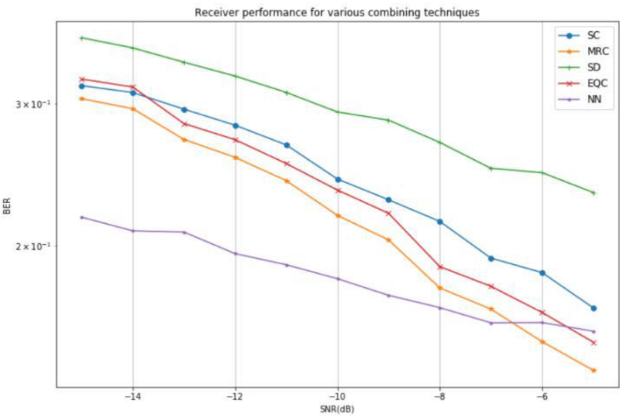

Figure-7. Low SNR for 2 branch.

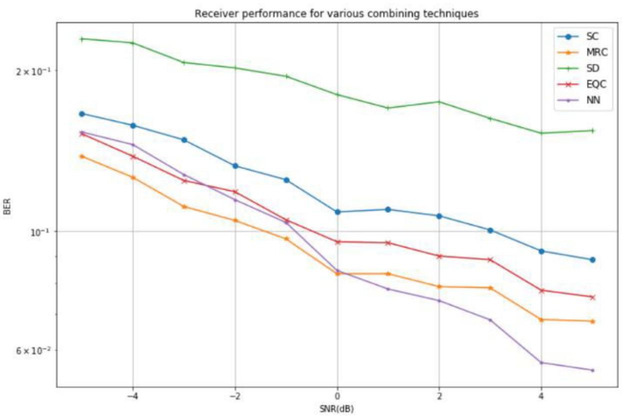

Figure-8. High SNR for 2 branches.

It is observed that roughly from the SNR range of 0 and upwards the neural network is the most efficient. After an SNR of roughly 13, it is 10 times better. Similarly, with the SNR values of -7 and downwards, the neural network method clearly outperforms other methods. Therefore, we have simulated for other receiver systems with more receivers. The simulations in the negative SNR range are given below. The simulations in the positive SNR range are also given below.

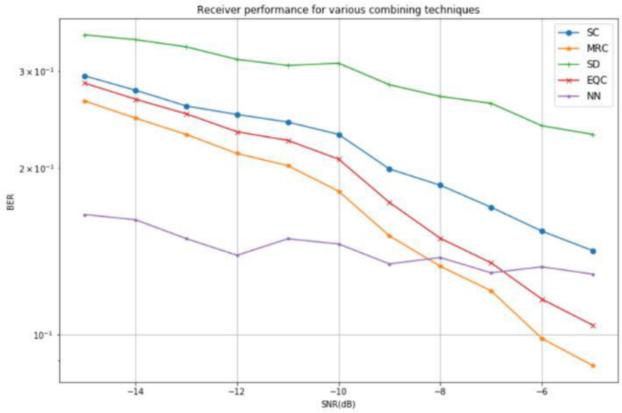

Figure-9. Low SNR for 3 branches.

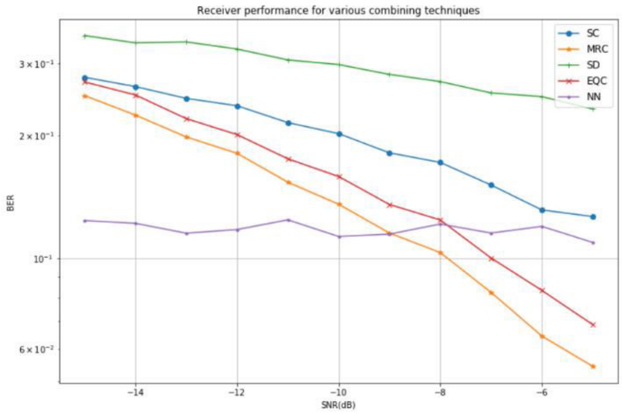

Figure-10. Low SNR for 4 branch.

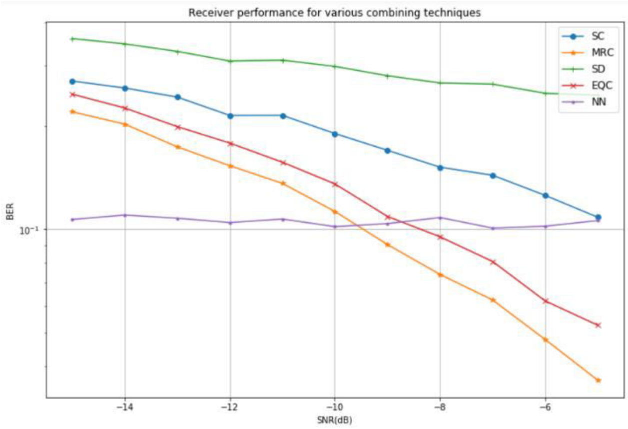

Figure-11. Low SNR for 5 branches.

VOL. 18, NO. 14, JULY 2023 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

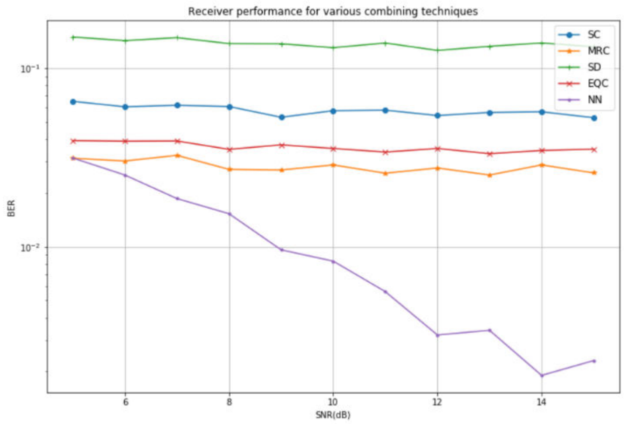

Figure-12. High SNR for 3 branches.

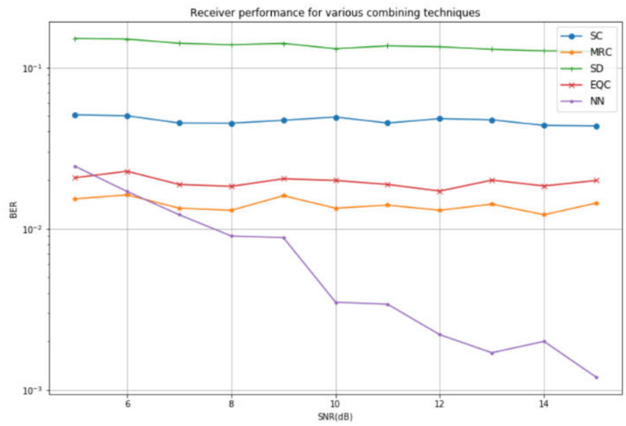

Figure-13. High SNR for 4 branches.

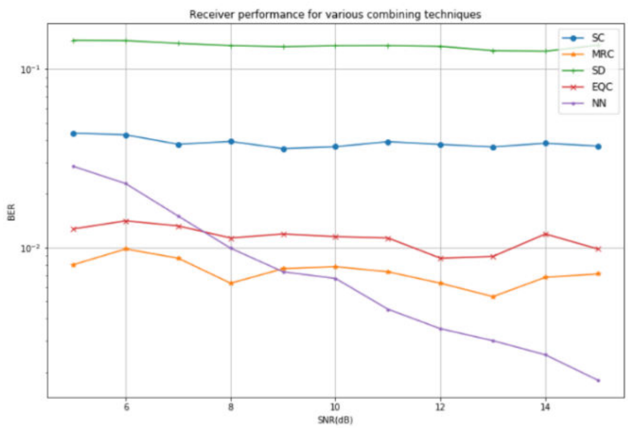

Figure-14. High SNR for 5 branches.

CONCLUSIONS

It can be seen from the Python simulation outputs plots that the use of neural networks for receiver diversity applications tends to give us better efficiency of communication. As the neural network trains on the data given, it works better in extreme signal-to-ratio cases. Therefore, it can be used in low signal power or high noise applications, and in high SNR environments. The trade-off of getting better efficiency is the increased amount of time taken. Even the simple neural network that we have used in this project is 1.5 to 2 times slowerthan the other methods. The circuitry might also tend to be a little more complex to accommodate neural networks. The use of binarized neural networks can make the circuitry even lighter and quicker. Neural networks can be beneficial in the field of communication engineering as the number of transmitters and receivers is only increasing and we are trying to improve communication every day by making it faster and with less latency. [15]

REFERENCES

[1] Roman Canizarez, Palacious Jativa, Azurdia-Meza, Montejo-Sanchez. 2022. Impact of diversity combining schemes in a multi-cell VLC system with angle diversity receivers. Springer.

[2] Andreia Pereira, Pedro Bento, Marco Gomes, Rui Dinis, Vitor Silva. 2018. Iterative MRC and EGC Receivers for MIMO-OFDM Systems. IEEE 87th Vehicular Technology Conference.

[3] Badarneh O. S., Alshawaqfeh M. K., Almehmadi F. S., Silva H. S. 2022. Selection combining over the extended fading channels. IEEE Wireless Communications Letters. 11(4): 722-726.

[4] Saito K., Ogawa Y., Nishimura T., Ohgane T., Hagiwara J. 2019, February. Computational Complexity Reduction of Receive Weight Matrices in Massive MIMO SC-FDF. In 2019 International Conference on Computing, Networking and Communications (ICNC) (pp. 16-21). IEEE.

[5] G ÖKC¸ E, M. C., BAYKAL, Y., YALC¸ ıN, A. T.A. 2022. Effects of receiver diversity on bit error rate of underwater optical wireless communication systems in weakoceanic turbulence.

[6] Zhang Q. T. 2021. Error rates for 4-branch equal- gain combining in independent Rayleigh fading: A simple explicit solution. IEEE Communications Letters. 26(2): 269-272.

[7] Khatoon H., Chidar R. K. 2019. Simulation and Performance Estimation of BPSK in Rayleigh channel using SC, MRC and EGC diversity techniques. Simulation. 6(02).

[8] Wang X., Cheng W., Zhang S. 2021, July. Effective capacity of multi-branch switched diversity systems over Fisher-Snedecor F composite fading channels. In 2021 IEEE/CIC International Conference on Communications in China (ICCC) (pp. 569-573). IEEE.

[9] Feng F., Na W., Jin J., Zhang J., Zhang W. and Zhang Q. J. 2022. Artificial neural networks for microwave computer-aided design: The state of the art. IEEE Transactions on Microwave Theory and Techniques.

[10] Shiotsu Y., Sugahara S. 2022. Binarized Neural Network Accelerator Macro Using Ultralow-Voltage Retention SRAM for Energy Minimum-Point Operation. IEEE Journal on Exploratory Solid-State Computational Devices and Circuits.

[11] Chi C, Jiang J. 2022. Logic Synthesis of Binarized Neural Networks for Efficient Circuit Implementation. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems.

[12] Vargas V. M, Gutierrez P. A, Barbaro-Gomez J, Hervaz-Martinez C. 2023. Activation Functions for Convolution Neural Networks: Proposals and Experimental Study. IEEE Transactions on Neural Networks and Learning Systems

[13] Liu X., Lin M., Kong H., Ouyang J., Cheng J. 2021. Outage performance for optical feeder link in satellite communications with diversity combining. IEEE Wireless Communications Letters. 10(5): 1108-1112.

[14] Bhardwaj P., Zafaruddin S. M. 2022. Performance of Hybrid Thzand Multi antenna RF System with Diversity Combining. IEEE Systems Journal.

[15] Nguyen L. V., Swindlehurst A. L., Nguyen D. H. 2021. Linear and deep neural network-based receivers for massive MIMO systems with one-bit ADCs. IEEE Transactions on Wireless Communications. 20(11): 7333-7345.

[16] Shiotsu Y., Sugahara S. 2022. Binarized Neural Network Accelerator Macro Using Ultralow-Voltage Retention SRAM for Energy Minimum-Point Operation. IEEE Journal on Exploratory Solid-State Computational Devices and Cir- cuit.