

Optimization of transmission signal by artificial intelligent

Hassan Farhan Rashag, Mohammed H. Ali

Technical Institute of Babylon, Al-Furat Al-Awsat Technical University, Iraq

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ABSTRACT

In this method, radial basis function network RBFNN is an artificial intelligent which is used to identify and classify the communication system performance. RBFNN is one type of neural network which has activation functions. It consists of three-layer input layer, hidden layer and output linear combination. One of the main problems of communication system is that it causes slow response for sending signal via the transmission devices. Therefore, the artificial intelligent by RBFNN is used to optimize the transmission signal. The input signal is trained and testing by neurons with weight and this lead to provide linear output. The simulation results have the optimization specifics over the traditional communication transmission devices.

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Corresponding Author:

Hassan Farhan Rashag,
Technical Institute of Babylon,
Al-Furat Al-Awsat Technical University,
Kufa, Iraq.
Email: Hassan_rashag@yahoo.com

1. INTRODUCTION

The concept of communication system is that sending the message at one point either exactly or approximately to another point [1]. In addition, the reliability of transmitting the message from the transmission source to a destination system based on channel by transmitter and receiver devices is discussed [2]. In order to derive the theoretically optimal solution in practice, source and receiver were consequently separated into numerous treating systems. This application is called sub-optimal [3, 4]. The sub-optimal has the benefit that any element can be separately evaluated and improved which gets actual effective and constant systems which is existing nowadays. Many reports focused on the optimization for transmit the signal with more effective [5-7]. Though recently, structures are improved over the previous years and it appears hard to achieve good system but any kind of station no need for calculated exhibiting with examination. [8, 9]. Other researchers developed method to enhance the signals features by using multiple cascades for transmission devices but this method has drawbacks like slow response and distorted carrier waves [10-12].

2. SIMULATION RESULTS

In this method, the RBFNN is chosen to optimize the transmission signals because it has many features over the neural network. These features are classification and identification the input signal by input and hidden layer to provide linear output signal. The structure of RBFNN is shown in Figure 1. In addition, the receiver constellation with equalizer learning curve based on bit error rate BER is shown in Figure 2. From this figure, the system is almost enhanced at BER = 0.49.

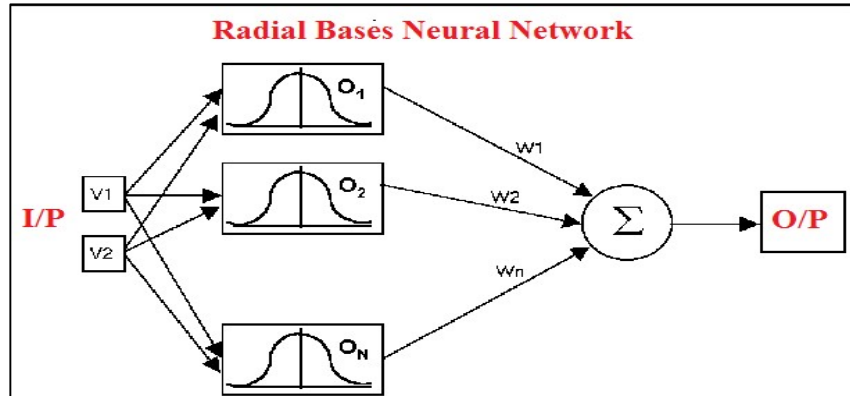


Figure 1. Structure of RBFNN

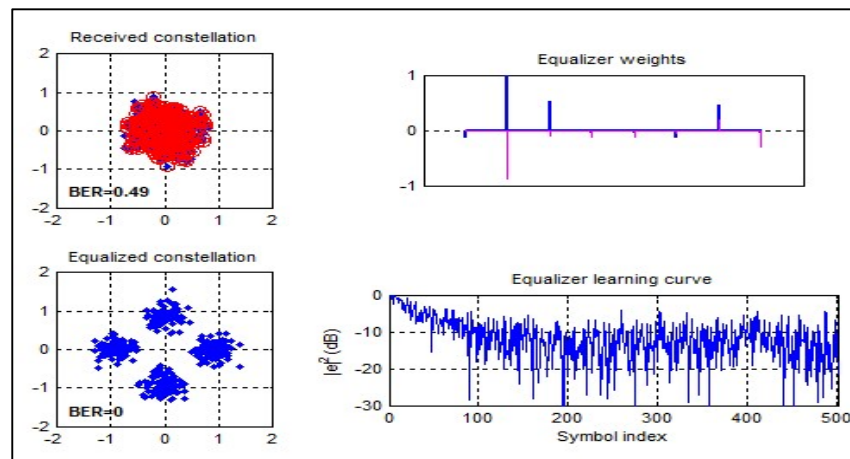


Figure 2. The receiver constellation at BER = 0.49

Figure 3 and Figure 4 show that the system with BER = 0.5, 0.52 respectively are more accurate and better for equalizer learning curve with high performance of receiver constellation.

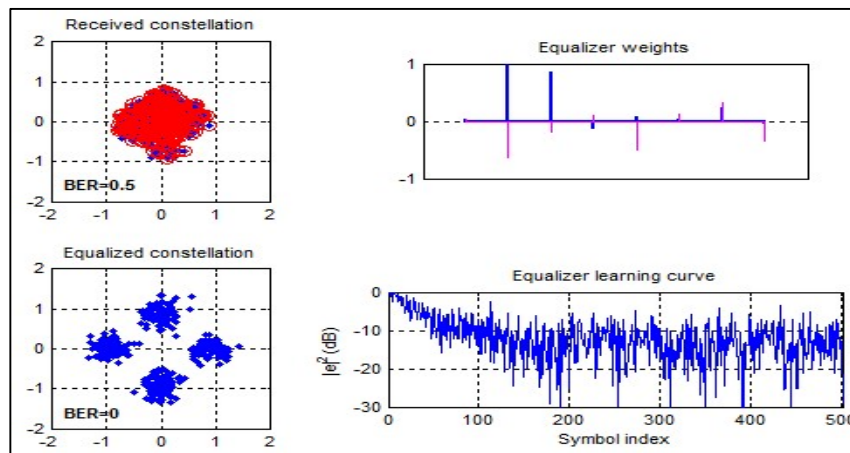


Figure 3. Receiver constellation at BER = 0.5

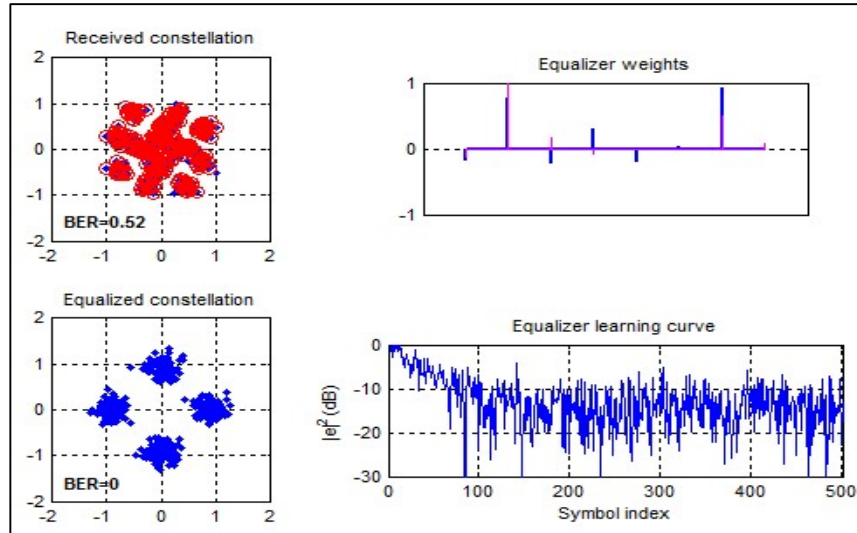


Figure 4. Equalizer learning curve at BER = 0.52

3. CONCLUSION

In this optimised method, the RBFNN is playing as an important tool for improved the communication system especially for transmission signal. The input signal is developed by activation function to minimize the distorted signal and to increase the response of transmission devices based on neurons and weight of hidden layer for RBFNN. The Simulink is built by tool box of matlab and the results is depended on difference values BER. finally, the system is better and optimized by high value of BER.

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