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Advanced neural network receiver design to combat multiple channel impairments

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Abstract: In communication systems, the channel noise is usually assumed to be white and Gaussian distributed. Therefore, an optimum receiver structure designed for the additive white Gaussian noise (AWGN) channel is employed in applications. However, in wireless communication systems, noise is often caused by strong interferences. Moreover, there are other effects such as phase offset that degrade the performance of the receiver. Designing the optimum receiver for different channel models is difficult and not reasonable because channel model and channel statistics are not known at the receiver. In this paper, we propose a neural network-based approach to demodulate the transmitted signal over unknown channels. Naturally, the collection of the training data, design and training of the neural network, and finally reconfiguration of the system according to the designed neural network are implemented on software-defined digital signal processing facilities. In particular, we show that the proposed receiver is capable of jointly canceling the strong interferences and phase offset. Simulation results in various signal environments are presented to illustrate the performance of the proposed system. It is shown that the proposed approach has the same performance as the correlation demodulator structure for AWGN channels, while it has a clear advantage for unknown channel models. Moreover, it is shown that the neural network-based receiver may be used for channel estimation and equalization over Rayleigh channels. Numerical results indicate that the performance of the proposed receiver is very close to the Rayleigh theoretical bound.

Key words: Neural network demodulator, software-defined radio, phase offset, interference, demodulation, Rayleigh fading channels

1. Introduction

Software-defined radio (SDR) is a very popular approach for improving the performance of conventional radio systems without requiring costly and time-consuming changes to physical hardware [1]. SDR is an adaptive solution for making communication systems flexible. The ideal SDR leads to a revolution in the design of the receiver with respect to the conventional receiver. In other words, SDR is a radio fully programmable in the baseband stage and entirely implemented digitally, so that it can be completely reconfigurable via software by employing digital signal processors (DSPs) [2]. The design of SDR-based receivers brings out exciting design challenges, particularly in energy-efficient communication systems [3]. SDR systems consist of analog-to-digital converter (ADC) and digital-to-analog converter (DAC) components. They transform baseband signals into passband signals at the transmitter. At the receiver, SDR generates samples of the baseband discrete time signal. Therefore, different intelligent computation techniques such as neural networks could be employed within these structures to improve the performance of the receivers. As in [4], one possible solution to apply a

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neural network-based demodulator is using a USRP (Universal Software Radio Peripheral) that is a flexible and affordable transceiver where the frequency range is 50 MHz to 2.2 GHz with frequency accuracy of 2.5 ppm. It has maximum instantaneous real-time bandwidth 16-bit sample width for 20 MHz while the maximum I/Q sampling rate is 16-bit sample width for 25 MS/s.

An information processing paradigm inspired by biological nervous systems is called the artificial neural network (ANN). It is applied to solve specific problems by using interconnected processing elements (neurons) working in unison [5]. Neural networks can be used to solve different types of problems with their remarkable ability to derive meaning from complicated or imprecise data [6,7]. Neural networks (NNs) play important roles in many engineering areas such as control, biomedical, electronics engineering, and recently communication engineering areas [8]. They are generally used to approximate unknown nonlinear functions by using their universal approximation, learning, and adaptation abilities. Active research has been done in NNs for communication systems [9,10] and several NN approaches have been proposed to design receivers [11–15]. In [11], despite using a large number of hidden neurons, the proposed NND (neural network demodulator) is shown to be suboptimal. Two other similar studies [12,13] and some more recent studies [14,15] considered the demodulation of digital modulated signals, such as amplitude shift keying (ASK) and quadrature amplitude modulation (QAM), and the performance of the system was only demonstrated by means of the learning curve of the NN. In [14,15] the authors utilized more complicated structures such as an Elman artificial NN and time-delay NN, and they stated that relatively large numbers of hidden layer neurons are required. In the above studies, the demodulation performance of the proposed NN-based systems was not investigated in terms of bit error rate (BER) as compared to theoretical BER curve of the respective modulation type. In addition, the parameters of the communication systems such as the effect of the noise level at the received signal, the number of pilot tones, and the effect of fading channel were not considered in these previous studies.

In our proposed NND system, the most simple and basic NN structure is used with only one hidden layer neuron. The performance of the proposed system is evaluated on both additive white Gaussian noise (AWGN) and Rayleigh channel conditions. Interfering signals are considered while evaluating the BER performance of the NN-based demodulator. We show that our proposed system approaches the optimal solutions obtained by the correlation receiver for AWGN channels. Our results for different channel imperfections are compared to theoretical BER limits of the BPSK modulation for AWGN and Rayleigh channels.

It is well known that reliable coherent data detection is not possible unless an accurate channel state information is available at the receiver [16]. In general the AWGN channel is considered to model the noise effects in wireless communication systems. However, in wireless communication systems, a strong interferer, which is colored in nature, dominates the noise model. For example, using various communication systems simultaneously occupying the current frequency spectrum leads to problems of interference between systems. Therefore, if interference is unavoidable, it causes high performance degradation at the receiver [17] and it has to be estimated and compensated [18].

Another undesired effect at the receiver is the phase offset that has to be recovered to improve the system performance. Therefore, it is necessary to obtain an estimate of the phase offset of the channel and then to rotate the symbols by this phase offset [19]. In the literature, corrupting effects such as interference and phase offset are investigated separately, and each problem introduces additional complexity at the receiver. It is clear that, in practice, all undesired effects have to be jointly considered and compensated at the receiver, hence increasing the computational burden.

In order to deal with the demodulation problem of transmitted signals over unknown channels where there are different types of undesired effects, we propose a NN-based SDR receiver that uses existing pilot tones for the training procedure.

Our goal is to develop a NN-based receiver that will account for the unknown random effect due to the presence of unknown interference and enable statistically efficient demodulation using a small number of pilot tones.

The rest of the paper is organized as follows. Section 2 introduces a conventional optimum receiver for the AWGN channel and then formulates the theoretical lower bound for BPSK modulations. Section 3 describes the proposed NN demodulator and our main assumptions concerning data transmission and channel model. We propose an improved receiver in the case of unknown channels. Section 4 illustrates the performance of the proposed receiver over different channel environments by means of computer simulations. Finally, Section 5 concludes the paper.

2. Conventional optimum receiver for AWGN channels

We assume that the transmitter sends digital information by using BPSK signal waveforms $\{s_1(t)\ s_2(t)$. Each waveform is transmitted within the symbol interval of duration T, $0 \leq t \leq T$ and the channel is assumed to corrupt the signal by introducing the AWGN.

$$r(t) = s_m(t) + \eta(t)\, 0 \leq t \leq T, m = 1, 2 \tag{1}$$

Here, $r(t)$ is the received signal, $s_m(t)$ is the transmitted signal, and $\eta(t)$ denotes a sample function of AWGN process with power spectral density $S_n(f) = N_0/2$ where N_0 is the noise spectral density. The $s_m(t)$ signals and corresponding basis function could be written as:

$$s_1(t) = \sqrt{\frac{2E_s}{T}}\sin(2\pi f_c t) = \sqrt{E}_s\phi(t), \tag{2}$$

$$s_2(t) = -\sqrt{\frac{2E_s}{T}}\sin(2\pi f_c t) = -\sqrt{E}_s\phi(t), \tag{3}$$

$$\phi(t) = \sqrt{\frac{2}{T}}\sin(2\pi f_c t), \tag{4}$$

where E_s is the symbol energy and is assumed as $E_s = 1$.

The main goal is to design a receiver that is optimum in the sense that it minimizes the probability of making an error for the conventional receiver. Therefore, the optimum receiver could be easily derived by using the maximum a posteriori probability (MAP) decision rule. In Figure 1, the optimum receiver is given. In this case, the theoretical bound for BPSK signaling could be written as follows [16] by using the constellation diagram given in Figure 2 while assuming that prior probabilities of transmitted symbols are equal.

$$P_b = Q\left(\sqrt{\frac{2E_b}{N_0}}\right) \tag{5}$$

Here, E_b is the bit energy and equals the symbol energy E_s, and standard error function $Q(.)$ is given as:

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int \lim_{x}^{\infty} e^{-\frac{t^2}{2}}\, dt. \tag{6}$$

The optimum receiver designed for AWGN will be called a correlation receiver for the rest of the paper because it is not optimum for unknown channels.

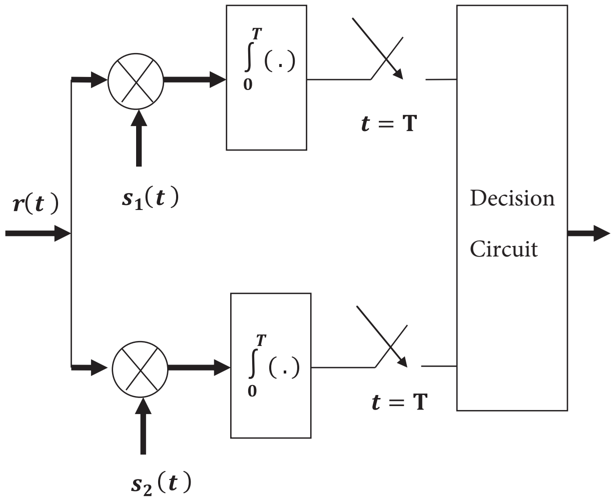

Figure 1. Correlation receiver for AWGN channel.

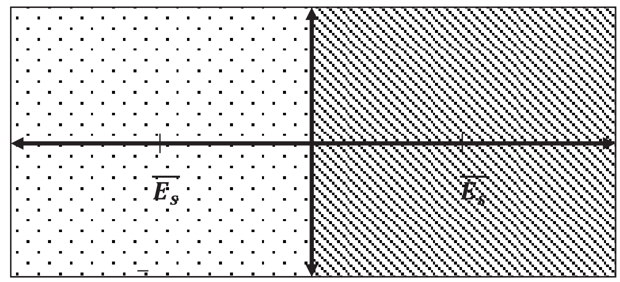

Figure 2. Constellation diagram of BPSK signals.

3. Proposed receiver

The proposed NND takes samples of the received signal in one symbol duration. A feedforward ANN is trained for all possible inputs of MPSK modulation symbols and the noise scenarios of the channel [20]. Then, by using this ANN, the transmitted data are detected by finding the maxima of the ANN outputs.

3.1. Input training data set generation

The input training data set is generated by considering the transmitted sequences between 0 and M − 1 periodically. Sequential and periodical transmission is preferred to guarantee and control presentation of each symbol equally in the input training data set. As $s_r[n]$ represents the received signal, $s_m[n]$ represents the information signal in one symbol period, $\eta[n]$ represents the channel noise, and sinusoidal formed MPSK signals are represented as follows for a fixed signal-to-noise power ratio (SNR):

$$s_r[n] = s_m[n] + \eta[n] \; r = 0, 1, \ldots M-1. \tag{7}$$

The received symbols are represented as:

$$s_r = \begin{bmatrix} s_r(0) \\ s_r(1) \\ \vdots \\ s_r(N_f-2) \\ s_r(N_f-1) \end{bmatrix}_{N_f \times 1} \quad r = 0, 1, \ldots M-1. \tag{8}$$

N_f is the number of samples in one symbol period. Unity input training data matrix S_u is generated by combining these M column vectors for M'ary modulation level:

$$S_u = \begin{bmatrix} s_0 & s_1 & \cdots & s_{M-2} & s_{M-1} \end{bmatrix}_{N_f \times M}$$

$$= \begin{bmatrix} s_0(0) & s_1(0) & \cdots & s_{M-2}(0) & s_{M-1}(0) \\ s_0(1) & s_1(1) & \cdots & s_{M-2}(1) & s_{M-2}(1) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ s_0(N_f-2) & s_1(N_f-2) & \cdots & s_{M-2}(N_f-2) & s_{M-1}(N_f-2) \\ s_0(N_f-1) & s_1(N_f-1) & \cdots & s_{M-2}(N_f-1) & s_{M-1}(N_f-1) \end{bmatrix}_{N_f \times M}. \tag{9}$$

By repeating this unity set K times for each level of the random channel noise $\eta_l[n]$, $l = 1, 2, \ldots, L$, we aim to get enough necessary data diversity for successful NN training where L is the total number of levels. After this process, the input training data set is expressed as follows:.

$$S_{u,l} = \begin{bmatrix} S_{u,l}^1 & S_{u,l}^2 & \cdots & S_{u,l}^{K-1} & S_{u,l}^K \end{bmatrix}_{N_f \times [M \times K]} l = 1, 2, \ldots, L, \tag{10}$$

where l represents the noise level.

Finally, the complete input training data set S_t is obtained as:

$$S_t = \begin{bmatrix} S_{u,1} & S_{u,2} & \cdots & S_{u,L-1} & S_{u,L} \end{bmatrix}_{N_f \times [M \times K \times L]}. \tag{11}$$

3.2. Target data set generation

To generate target training data sets, 1 is used to represent expected output values and –1 for others. These numbers represent numerically the answer of the question: "Are the transmitted data detected?" The answer YES is represented by 1 where the answer NO is represented by –1. The target training data sets of a single NN having M output are given. Each column vector detects a single symbol reception relatively from 0 to $M-1$.

$$t_0 = \begin{bmatrix} 1 \\ -1 \\ -1 \\ \vdots \\ -1 \\ -1 \end{bmatrix}_{M \times 1} \quad t_1 = \begin{bmatrix} -1 \\ 1 \\ -1 \\ \vdots \\ -1 \\ -1 \end{bmatrix}_{M \times 1} \quad \ldots t_{(M-1)} = \begin{bmatrix} -1 \\ -1 \\ -1 \\ \vdots \\ -1 \\ 1 \end{bmatrix}_{M \times 1} \tag{12}$$

"Unity" target training data set T_u is generated by collecting/combining these M column vectors for M'ary modulation level.

$$T_u = \begin{bmatrix} t_0 & t_1 & \cdots & t_{M-2} & t_{M-1} \end{bmatrix}_{M \times M} = \begin{bmatrix} 1 & -1 & \cdots & -1 & -1 \\ -1 & 1 & \cdots & -1 & -1 \\ -1 & -1 & \cdots & -1 & -1 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ -1 & -1 & \cdots & 1 & -1 \\ -1 & -1 & \cdots & -1 & 1 \end{bmatrix}_{M \times M} \tag{13}$$

By repeating this unity set K times for each level of the random channel noise $\eta_l[n]$, $l = 1, 2, \ldots, L$, we aim to get enough necessary data diversity for successful NN training. Similarly, the unity target training data set repeats itself K times:

$$T_l = \begin{bmatrix} T_l^1 & T_l^2 & \cdots & T_l^{K-1} & T_l^K \end{bmatrix}_{M \times [M \times K]} l = 1, 2, \ldots, L. \tag{14}$$

Finally, target training data set T is obtained as follows:

$$T = \begin{bmatrix} T_1 & T_2 & \cdots & T_{L-1} & T_L \end{bmatrix}_{M \times [M \times K \times L]}. \tag{15}$$

3.3. Neural network demodulator design

Feedforward multilayer NNs are used to design the proposed NND. The total number of samples in one symbol period is selected as $N_f = 16$. This means that the designed NND has 16 inputs. A single hidden layer neuron is used for comparison, and two output layer neurons are used for symbol detection in BPSK. Two hidden layer neurons are used for comparison, and M output layer neurons are used for symbol decision for higher PSK levels. NND hidden layer neurons are selected by considering the I-Q (in-phase and quadrature-phase) demodulator's correlation processing complexity. A single correlation process is sufficient for BPSK. However, two correlation processes are necessary to obtain in-phase and quadrature-phase components for higher levels of MPSK. These two correlation processes' complexities are equal to the multiplication of NN inputs by weights of two neurons. The remaining part of the NND demodulator needs 2 times (weights of each output neuron) M multiplication, but the I-Q demodulator needs higher complexity to filter higher harmonics of sinusoidal multiplication of correlation processes. By assuming the equality of the constellation diagram mapping complexities of each case, it may be concluded that the NND has lower complexity than the I-Q demodulator.

There are many possible activation functions in NNs. In our extensive experimental studies, we observed that the tangent sigmoid transfer function gives the best results for both layers (Figure 3). We also observed that Levenberg–Marquardt optimization yields the best results to train the designed network. Therefore, in the proposed structure, tangent sigmoid transfer functions are used for both layers and Levenberg–Marquardt optimization is employed to train the designed network.

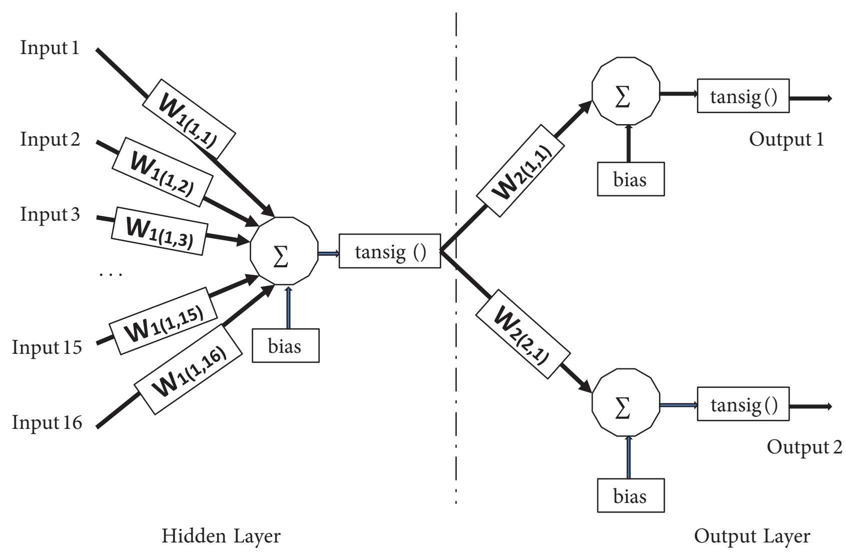

Figure 3. Proposed neural network structure for BPSK.

4. Simulation results

This section presents the results of computer simulations of the proposed methods for different channel environments. One of the most important things is the number of pilot symbols. The other is the selection of the SNR level to generate the training data set. These are detailed in Section 4.3. According to the examined results, the number of pilot tones is selected as 2048 and training data set generation SNR levels are 0 dB in Sections 4.1, 4.2, and 4.4. The proposed operational data frame structure is given in Figure 4 and imagination of the possible implementation strategies and some calculations are left to the reader and future works. The practical issues such as hardware specifications and necessities for the training sequence collection and training environment are also left for future studies in the field. The main objective of this study is to justify the use of NNs as demodulators and their performance results over some known and unknown channels.

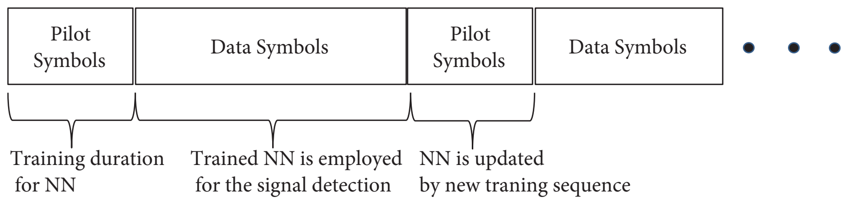

Figure 4. Frame structure for NN receiver.

Symbol period is chosen as $T = 0.01s$ and the carrier frequency is chosen as $f_c = 100Hz$. Sampling time is chosen as $T_s = 1/1600$ s to generate $N_f = 16$ samples for each symbol.

4.1. AWGN channel case

First we investigate the performance of the proposed scheme by employing BPSK modulation over the AWGN channel. Figure 5 shows the BER performance of the proposed receiver. As such, we also included the performance of the optimum receiver and the theoretical bound of BPSK demodulation for the AWGN channel. It is shown in the figure that the proposed NN receiver achieves the same performance as the optimum receiver for the AWGN channel.

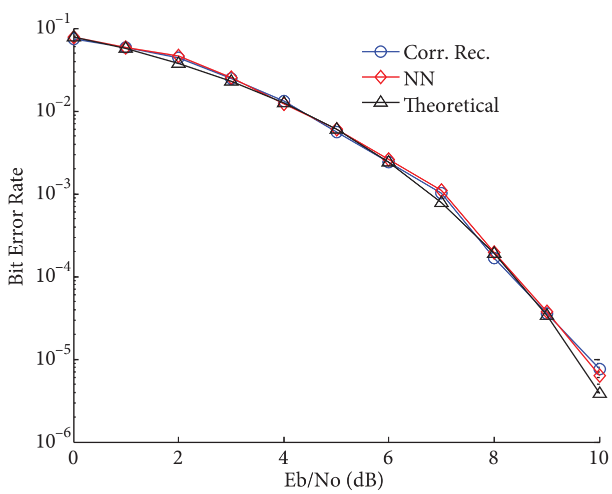

Figure 5. BER comparison of proposed receiver and correlation receiver for AWGN channel.

4.2. Multiinterference Case

To test the performance of our receiver over other channel environments, interfering signals are added to the transmitted signal and error performance is evaluated. The signal model is revised as:

$$r\,(t) = s_m\,(t) + \eta(t) + i_1(t) + i_1(t), \tag{16}$$

while $i_1(t) = \alpha_1 cos(2\pi f_c t + \phi_1)$ and $i_2(t) = \alpha_2 cos(2\pi f_c t + \phi_2)$. The frequencies of the interferences are chosen to be the same as the carrier frequency to make them difficult to be eliminated by conventional filtering methods. The amplitudes and the delays of the interferences are selected arbitrarily as demonstrated in Figure 6. It is again observed that the proposed SDR receiver based on a NN has a compatible performance with the theoretical bound of the AWGN channel. It is shown in Figure 7 that the proposed NN-based SDR receiver outperforms the existing correlation receiver that does not account for the interference. It exhibits a gain of about 2 dB over the correlation receiver. It is also shown that the performance difference between the proposed and correlation receivers increases for higher SNR values.

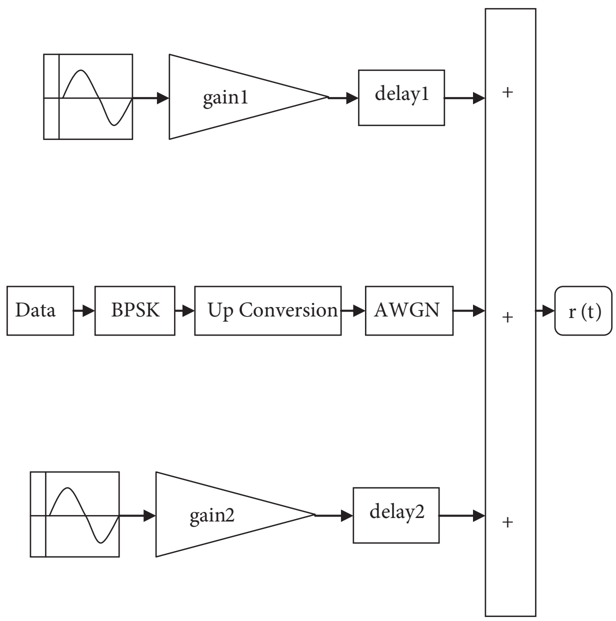

Figure 6. Multiple interference addition.

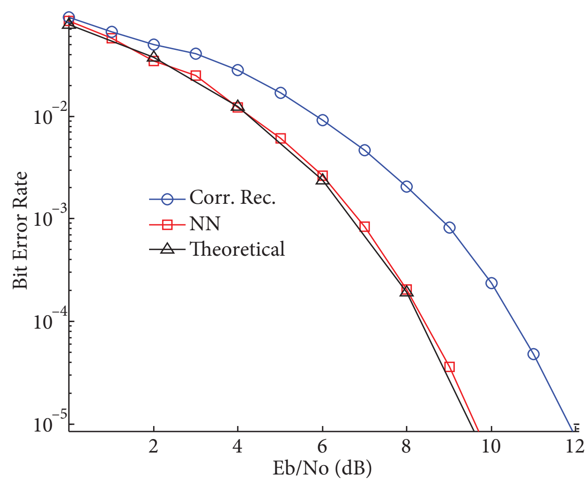

Figure 7. BER comparison of proposed receiver and correlation receiver for multiple interferers.

4.3. Multiinterference and phase offset case

It is not practically possible to make the receiver phase offset exactly match the transmitter. A difference in the phase of the local oscillators in the transmitter and receiver causes the uncertainty at the receiver. Since the phase offset result in a time-varying rotation of the data symbols, it causes a large performance decrement in terms of BER. In the presence of phase offset, additive noise, and multiple interferences, the received signal at the receiver is:

$$r(t) = s_m(t)\, e^{j(\theta_0)} + \eta[t] + i_1(t) + i_2(t), \tag{17}$$

where θ_0 is the phase offset and is selected as $\theta_0 = \pi/8$. At the receiver, phase offset of the channel should be estimated and compensated while canceling the interference simultaneously.

It is again observed that the proposed SDR receiver can reach a compatible performance with the AWGN theoretical bound. The performance of the NND is affected by two issues: the training data set SNR level and the number of pilot tones. The SNR level of the training sequence should be carefully selected to optimize the number of required pilot symbols. When the training SNR is closer to zero, better performances are achieved with fewer pilot tones. On the other hand, when the training SNR set is chosen with a small noise level (SNR$>5dB$), the performance degrades for the same number of pilot tones because NN learning ability is directly related to data diversity. Figures 8–10 show the proposed receiver's performances for 256, 1024, and 2048 pilot tones at 10 dB measurement level. On the other hand, the training SNR effect will diminish when the total number of pilots is increased, as shown in Figure 10. Consequently, two conditions have to be simultaneously satisfied to achieve a desired performance: in the training phase, the SNR level has to be lower than 5 dB and preferably close to zero; and the necessary number of pilot tones has to be collected. Between 0 and 5 dB, 2048 pilot tones are sufficient to reach the theoretical error bound. If we use 1024 pilot tones, the differences between the theoretical bound and the NND performance are less than 1 dB for the same interval. Even by using only 256 pilot tones, the NND performs about 2 dB better than the correlation receiver. According to these results, it can be concluded that the NND may be used in practical SDR applications.

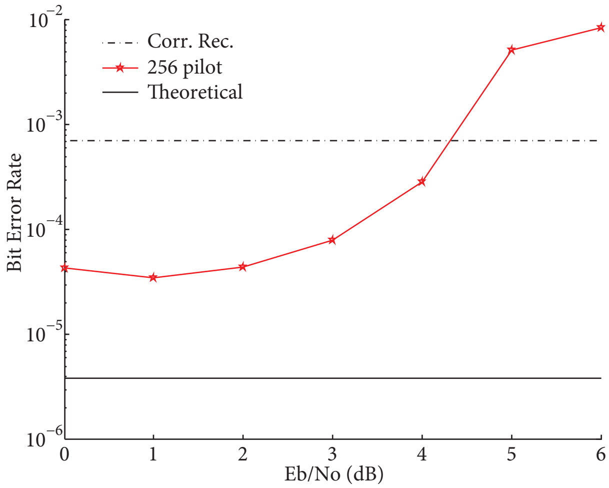

Figure 8. Effect of the training data collection from different SNR levels: it is obtained for 256 pilot symbols and measured at 10 dB.

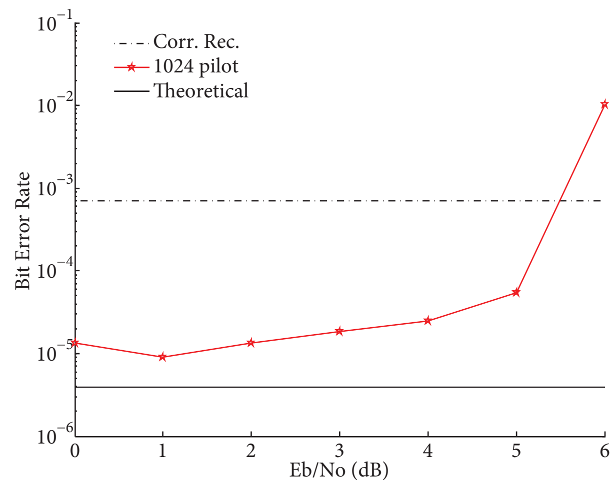

Figure 9. Effect of the training data collection from different SNR levels: it is obtained for 1024 pilot symbols and measured at 10 dB.

4.4. Rayleigh channel case

In a multipath environment, Rayleigh fading is a specific type of signal fading when there are many objects in the environment that scatter the radio signal before it arrives at the receiver and there is no dominant propagation along a line of sight between the transmitter and receiver. A Rayleigh fading channel can be modeled by generating the real and imaginary parts of a complex number according to independent normal Gaussian variables.

The Rayleigh fading effect caused by multipath reception has to be estimated and equalized at the receiver. Therefore, channel estimation is a crucial part of the receiver structure and it is generally focused on using pilot symbols. In practical systems, channel estimation is done for the pilot duration and the estimated channel is employed to equalize the received signal for data duration. In [21], a channel estimation technique based on multilayer perceptron NNs was proposed for a space-time coded MIMO-OFDM system. The simulation results showed that the performance of the NN was better than that of least square and least mean square error algorithms. In this section, pilot symbols are employed to train the NN-based receiver. Therefore, the NN is trained for joint channel estimation and equalization processes. In other words, the NN receiver directly calculates the necessary coefficients to equalize the received signals.

The signal model is given as follows:

$$r(t) = h(t) . s_m(t) + \eta(t), \tag{18}$$

where the channel response $h(t)$ has a Rayleigh distribution. In our simulations, a quasistatic Rayleigh channel is considered where the channel remains constant for a block of transmission, and this constant within blocks varies independently. A new NND is designed for each channel condition and its performance is calculated by changing the AWGN noise level between 0 and 45 dB by 5 dB increments. The performances of all receivers are tested for 2000 different channels and are displayed in Figures 11–13 for BPSK, QPSK, and 8PSK modulation schemes, respectively. The NN structure used for QPSK and 8PSK is given in Figure 14. For each symbol, 128 pilot tones are sufficient for 4–8PSK levels at 0 dB training SNR level. Numerical results indicate that the performance of the proposed receiver is very close to the Rayleigh theoretical bit error lower bound, which is given by:

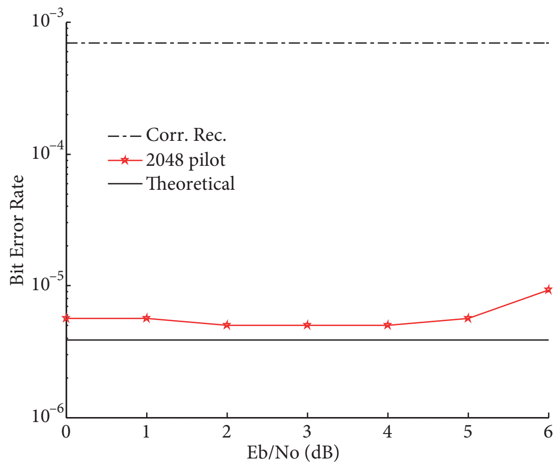

Figure 10. Effect of the training data collection from different SNR levels: it is obtained for 2048 pilot symbols and measured at 10 dB.

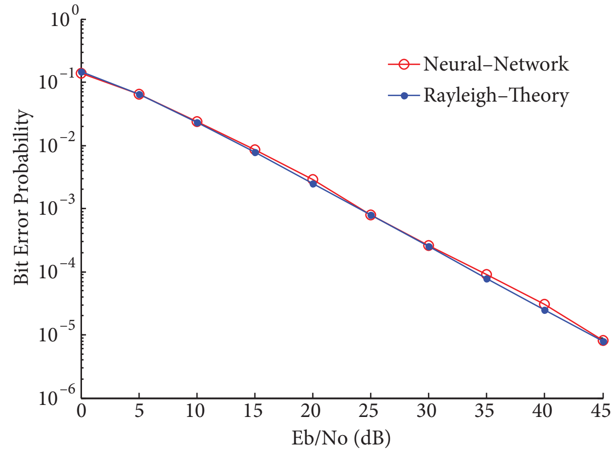

Figure 11. Rayleigh channel performance results of NND for BPSK.

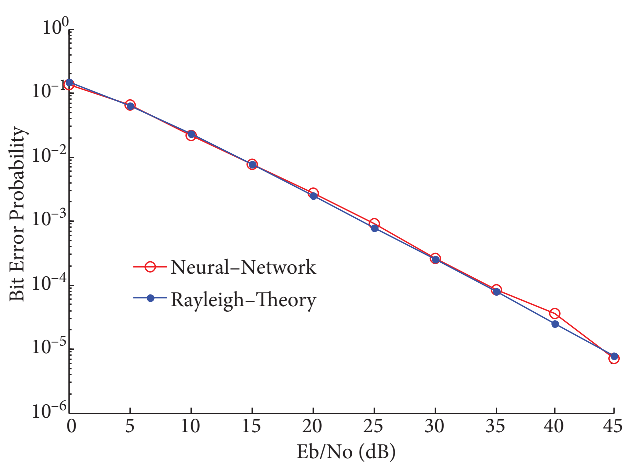

Figure 12. Rayleigh Channel performance results of NND for QPSK.

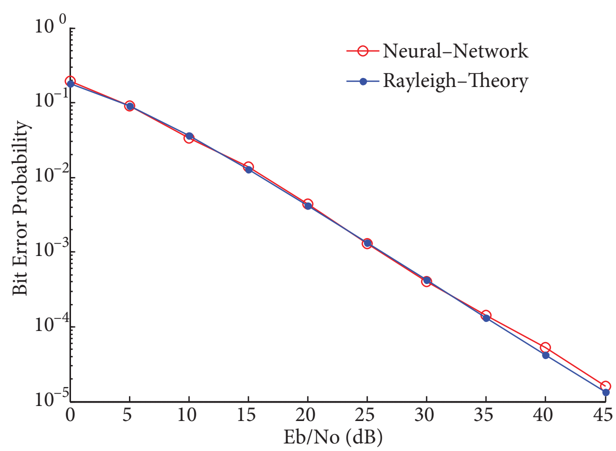

Figure 13. Rayleigh channel performance results of NND for 8PSK.

$$P_b = \frac{1}{2}\left(1 - \sqrt{\frac{(E_b/N_0)}{(E_b/N_0)+1}}\right). \tag{19}$$

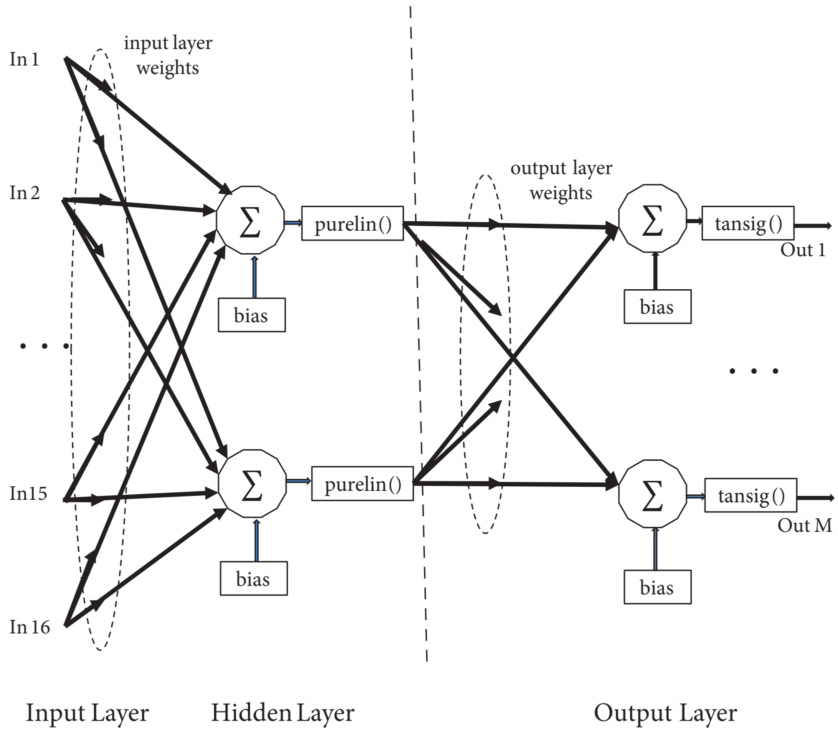

Figure 14. The NN structure used for QPSK and 8PSK.

5. Conclusions

In this paper, we investigated the problem of signal demodulation in a practical wireless communication system where the receiver has only access to a noisy estimate of the channel provided by training symbols. We proposed a NN-based SDR receiver that takes into account the unknown channel model by training sequence. Our numerical results indicated that the proposed receiver has the same performance as the correlation receiver for the AWGN channel while it has a clear advantage for interference and phase offset channels. It was shown that the proposed receiver could estimate and jointly cancel these undesired effects. Moreover, it was also shown that the proposed receiver could be used for fading channels. This performance improvement is obtained at the expense of additional complexity caused by the NN structure in the receiver. However, it is clear that additional complexity is reasonable for practical systems while cancelation of these effects by many methods in the literature requires more complexity, yet they are not capable of canceling these effects simultaneously. It is also shown that there is a tradeoff between the total number of training symbols and the system performance.

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