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Research Article

Deep Learning Based Mapping Diversity

Burak TÜRER[1], **Mümtaz YILMAZ**[2*]

[1]*Aydın Adnan Menderes University, Graduate School of Natural and Applied Sciences, Aydın, TÜRKİYE*
[2]*Aydın Adnan Menderes University, Faculty of Engineering, Department of Electrical&Electronics Engineering, Aydın, TÜRKİYE*

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Abstract

In this work, the mapping diversity technique, applied to enhance the bit/symbol error rate performance in wireless fading channels, is designed using deep learning based autoencoder. Specifically, the multiple signal constellations required in mapping diversity technique are obtained using autoencoder structure. In this framework, the multiple signal constellations, obtained by assuming multiple channel use in autoencoder structure, are used in mapping diversity and the performance of this proposed system is compared with classical repetitive transmission technique. Design and simulations are repeated for different modulation types and thereby, the performance of the proposed system is investigated for various data rates under fading channel conditions. Consequently, supported with simulation results, the proposed deep learning based mapping diversity technique is shown to attain better performance than classical repetitive transmission technique.

Keywords

"Deep learning, Mapping diversity, Autoencoder, Fading channel"

**** Corresponding Author:*** ***mumtaz.yilmaz@adu.edu.tr***

1. Introduction

Transmitting the same information through multiple independent paths has the potential to improve the bit/symbol error rate of a wireless communication link degraded by channel conditions. Instead of simply retransmitting multiple copies of the original data, rearranging the constellation diagram and employing a modified constellation diagram can achieve diversity gain. This technique is generally referred to as mapping diversity in the literature. In the seminal work in this field by Metzner (1977), an additional performance improvement was achieved by using a second transmission block derived from the first block, in combination with multilevel amplitude and phase modulation for non-binary block codes. In the Automatic Repeat Request (ARQ) protocol, the transmitter is requested to resend the packets identified as received erroneously. Retransmission continues until the erroneously sent packet is correctly received or the predefined maximum number of transmissions is reached. In this context, the ARQ technique is a natural application area for the implementation of mapping diversity. In the work by Benelli (1992) the Euclidean distance was increased by using two different mappings, resulting in an overall performance improvement in the ARQ system. In another study by Samra et.al (2005), different symbol mappings optimized to minimize the bit error rate for each packet transmission were employed for non-binary modulation schemes.

In the Hybrid ARQ method, which is a natural extension of the ARQ technique, the channel coding block is incorporated into the ARQ structure and has been standardized within third-generation cellular communication systems through high-speed downlink packet access technique (Wengerter et al., 2002). In this work, constellation rearrangement (an alternative term for mapping diversity) is employed using a total of four different mappings to equalize the reliabilities of different bits within the same symbol. In the case of using the same symbol set for repeated transmissions of the same symbol, the difference in reliabilities between different bit positions naturally increases, making such equalization necessary. In the same study, (Wengerter et al., 2002), a total of four different mappings were used for the 16-Quadrature Amplitude Modulation (QAM) modulation scheme in an additive white Gaussian noise (AWGN) channel, and the likelihood ratios of all bits were equalized. A review of the literature reveals that the constellation rearrangement technique has been implemented using two different methods. In the first method, the bit-to-symbol mapping rule remains the same for all transmissions, while the positions of the signals in the constellation set can be altered. In the second method, the same constellation set is used for all transmissions, while the bit-to-symbol mappings can be varied.

Artificial intelligence has recently become a research topic of increasing interest and finds application across all layers of wireless communication systems, including the physical layer. A review of the literature reveals that the studies are fundamentally divided into two categories: machine learning-based and deep learning-based. In the review study on machine learning in wireless communication systems by Chen (2019), the application areas of artificial neural network-based machine learning in wireless networks are provided. In this work, these areas are identified as prediction, interference, big data analytics, and self-organizing networks. In another significant study (Simeone, 2018), the applications are categorized under two main headings: applications at the edge and in the cloud of the wireless network, separately for supervised and unsupervised learning. When we consider the applications of deep learning techniques, which can be described as an advanced form of machine learning, in wireless communication systems, the study by Dai et al. (2020) addresses transmitter and receiver design under the heading of deep learning-based architecture design for wireless communication, and channel estimation, decoding, and optimization solutions. In studies focused on the physical layer (Wang et al., 2017; Qin et al., 2019; Kim et al., 2020), deep learning has been utilized to provide solutions for modulation recognition, channel coding and decoding, and detection/estimation in wireless communication systems.

In classical communication systems, operations such as source coding, channel coding, modulation, demodulation, and channel estimation in the physical layer are typically performed by corresponding independent blocks. In this structure, since each block is optimized separately, the best possible end-to-end performance may not be achieved (O'Shea & Hoydis, 2017). On the other hand, in an artificial intelligence-based communication system, particularly one leveraging deep learning, transmitter, receiver, and channel can be jointly optimized as a single end-to-end block without the need for separate blocks (O'Shea&Hoydis, 2017; O'Shea vd., 2016). This approach is expected to achieve objectives such as lower bit error rates, higher bandwidth efficiency, and reduced energy consumption.

Autoencoder (AE) is basically a feedforward neural network which forms the foundation of deep learning (Goodfellow et al., 2016). An autoencoder is essentially a feedforward neural network that tries to reconstruct its input signal at the output using an unsupervised method. Traditionally, autoencoders have been used for dimensionality reduction and feature learning. By design, an autoencoder learns how to ignore noise in the data, thereby reducing data dimensions. The autoencoder neural network is adjusted to ensure that the target values at the output are equal to the input values with minimal loss. Communication systems can be characterized as autoencoders in which the transmitted message is reconstructed at the receiver with minimal error. In this study, the idea of implementing constellation optimization using an autoencoder was adopted. A deep learning-based autoencoder was trained, and the resulting constellation sets were utilized in the mapping diversity technique. The performance of the designed autoencoder-based mapping diversity technique was analyzed for fading channel, and the system performance was compared with the classical retransmission method for different modulation schemes. The organization of the study is as follows: After presenting the general system structure in the second section, the simulation results are given in the third section. The study concludes with the fourth section, which presents the results.

Symbols and Abbreviations

ARQ	*Automatic Repeat Request*
QAM	*Quadrature Amplitude Modulation*
PSK	*Phase Shift Keying*
AWGN	*Additive white Gaussian Noise*
AE	*Autoencoder*
E_b	*Energy per bit*
E_s	*Energy per symbol*
N_0	*noise power spectral density*
R	*information rate*

2. System Structure

As stated in the introduction, the aim of this study is to implement the mapping diversity technique using a deep learning-based autoencoder. Therefore, while explaining the system structure, the design of a typical communication system using an autoencoder will first be presented, followed by the explanation of the mapping diversity technique. As shown in Figure 1, the autoencoder consists of five components: input, encoder, bottleneck, decoder, and output. The input section consists of the data to be encoded and fed into the system. In the encoder section, the model learns how to reduce the input dimensions and compress the input data into an encoded representation. The bottleneck section contains the compressed representation of the input data. The data in this section is the most compact form of the input data. In the decoder section, the autoencoder learns how to reconstruct the data from the encoded representation to be as close as possible to the original input. In the final section, the output, the loss of the system is reviewed through reconstruction, and the performance of the decoder is evaluated by measuring how close the output is to the original input. Consequently, the data closest to the input is generated. To achieve an output identical to the input, the described processes are performed sequentially, and the neural network is trained.

It is possible to learn and implement a communication system in an end-to-end manner using a deep learning-based autoencoder. In the basic block diagram of a classical communication system, the transmitter, channel, and receiver can be optimized within a single structure using an autoencoder. As shown in Figure 2, the channel coding, source coding, and modulation processes performed at the transmitter are carried out in the encoder section, while the decoding and demodulation processes performed at the receiver are handled in the decoder section. In this way, inputs are first compressed in a nonlinear manner and then reconstructed (O'Shea & Hoydis, 2017). The main idea here is to represent the transmitter, channel, and receiver as a deep neural network that can be trained with an autoencoder (O'Shea & Hoydis, 2017). In short, an autoencoder is a deep neural network that consists of an encoder, which encodes the data coming from the transmitter, and a decoder, which reconstructs the inputs using the encoded data (Erpek et al., 2020).

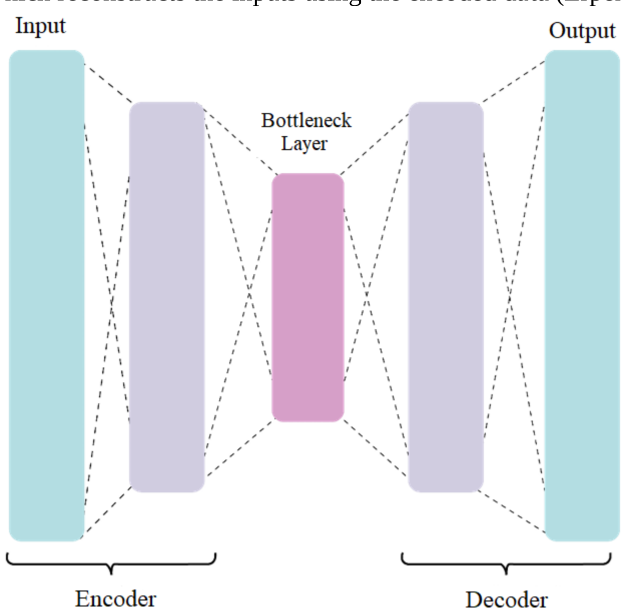


Figure 1. Components of Autoencoder.

The structure referenced in the design of the deep learning-based communication system is shown in Figure 2. The main goal is to transmit the information signal $m \in \mathbb{M}$, which is an element of the message set $\mathbb{M}=\{1,2,..M\}$, from the transmitter to the receiver over the communication channel without error. Each information signal consists of $k = \log_2 M$ bits. The message signal, *m*, selected from the information signal set with a total of *M* elements, is transmitted to the receiver using the channel a total of *n* times.

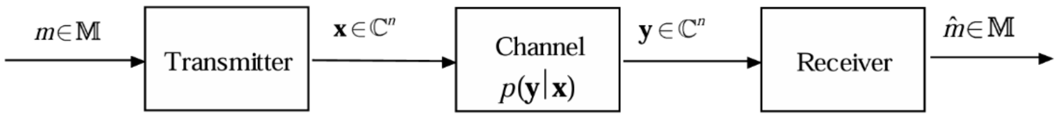


Figure 2. Block diagram of deep learning-based communication system

If we denote the vector **x**, transmitted from the transmitter and consisting of a total of n complex symbols, as $\mathbf{x} = [x_1, x_2, \ldots, x_n]$, where each x_i symbol consists of k bits, the information rate R is calculated as $R=k/n$ [bits/channel use]. Before transmission, the vector **x** is subjected to a power constraint of the form $\|\mathbf{x}\|_2^2 \leq n$ or an average energy constraint of the form $\mathrm{E}[x_i^2] \leq 1,\ \forall i$. Here $\|\mathbf{x}\|_2^2$ value shows the Euclidean norm of vector **x**. $\mathbb{C}^n$ denoting the set of n-dimensional complex numbers, the noisy and distorted version of the transmitted signal $\mathbf{x} \in \mathbb{C}^n$, represented as $\mathbf{y} \in \mathbb{C}^n$, is observed at the receiver, and the estimate, $\hat{m} \in \mathbb{M}$, of the original message signal s is obtained. Accordingly, Pr (.) denoting the probability value; the symbol error rate in the system is given as:

$$P_e = \frac{1}{M} \sum_m Pr\ (\hat{m} \neq m | m) \tag{1}$$

Under the assumption of a noisy channel, given the general diagram in Fig.2, the structure of the communication system redesigned with an autoencoder is shown in Fig. 3. In this design, the transmitter section is modeled as a multilayer artificial neural network, with the input of this network being the information signal to be transmitted to the receiver. The information signal at the input of the artificial neural network is defined as an M-dimensional vector, where the m-th element is 1, and all other M-1 elements are 0. Mathematically, this vector can be represented as $\mathbf{1}_m \in \mathbb{R}^M$, where $\mathbb{R}^M$ denotes the set of M-dimensional real numbers. The transmitter block consists of multiple dense layers and a final normalization layer. With the help of this structure, operations such as source coding, channel coding, and modulation, which are traditionally designed as separate blocks in the classical communication block diagram, can be optimized simultaneously and in a synchronized manner. As the final operation in the transmitter block, the signal to be transmitted is passed through the normalization layer. In the channel block, the transmitted signal is affected by a multiplicative fading coefficient, followed by the addition of an AWGN noise component (Proakis, 2008). When the energy per bit (E_b) to noise power spectral density (N_0) ratio is denoted as E_b/N_0 and the information rate as R, the channel variance is found as $N_0/2RE_b$.

The receiver section is designed similarly as a feedforward neural network consisting of a single or multiple dense layers followed by a softmax activation layer. In classical communication systems, the functions performed by blocks such as demodulation, channel decoder, and source decoder in the receiver are carried out in this structure by the deep learning layers. Finally, the output signal is passed to the softmax layer. The softmax layer, also known as the classification layer, provides the probability of the input belonging to a specific class, ranging from a minimum of 0 to a maximum of 1. Consequently, at the output of the neural network in the receiver, an M-dimensional probability vector $\mathbf{p} \in (0,1)^M$ is obtained, containing the probability values for all possible messages. The index of the highest probability element in the **p** vector determines the estimated message, $\hat{m}$.

Table 1 lists the activation function types and output dimensions for each layer in the model configuration, which is constructed by combining the layers in the sequence specified in the table. The first to fourth layers constitute the transmitter side of the system. The fifth layer represents the noisy channel layer between the transmitter and the receiver. The sixth and seventh layers form the receiver side of the system. The estimated message is obtained from the output of the Softmax layer in this structure.

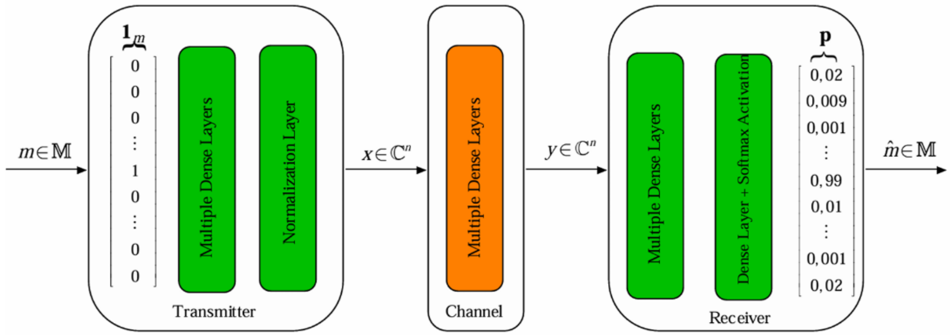


Figure 3. The structure of a communication system designed with an autoencoder

Table 1. The architecture of autoencoder model

Layers	Output Size
Input	M
Dense + ReLU	M
Dense + Linear	2n
Normalization	2n
Channel	2n
Dense + ReLU	M
Dense + Softmax	M

The geometric arrangement of symbols in the constellation set, defined as the set encompassing all possible symbols to be transmitted from the information source, affects the symbol error rate of the entire system. For a constellation set where each symbol consists of $k = \log_2 M$ bits, there are a total of M elements. The mapping diversity technique is based on the principle of using different constellation sets to reduce the bit/symbol error rate, rather than using the same constellation set for multiple transmissions of the same symbol. In the mapping diversity technique, the signal space is designed by taking the bit error rate as the optimization target function, aiming to obtain a signal set that minimizes this value. In this study, it is assumed that the same symbol is transmitted twice (N=2), and therefore two different constellation sets are used in the mapping diversity technique. In the deep learning-based mapping diversity technique designed in this study, two different constellation sets were obtained within the signal autoencoder structure by setting the channel usage value to n=2. For comparison purposes, in the reference system used in the simulations, the same symbol was transmitted twice, but the same classical constellation set corresponding to the modulation type was used for both transmissions.

3. Simulation Results

As stated in the second section, the performance of the mapping diversity technique designed using a deep learning-based autoencoder was compared with a reference system where mapping diversity was not applied; in other words, the same classical constellation sets were used for both transmissions. As can be observed in the literature, mapping diversity is applied to high-order modulation schemes due to the design flexibility it provides and achieves higher performance improvements, particularly in square QAM modulation schemes such as 16-QAM and 64-QAM. For these reasons, the simulations were conducted for the 8-PSK (Phase Shift Keying), 16-QAM, and 64-QAM modulation schemes.

Accordingly, since the channel usage value is n = 2, the information rates are 3/2 bits/channel use for 8-PSK, 2 bits/channel use for 16-QAM, and 3 bits/channel use for 64-QAM. During the training of the autoencoder, the Adam optimization algorithm was applied. Two different training dataset sizes (100 and 1000) and two different learning rates (0.001 and 0.0001) were used during training. The number of iterations for all training phases was set to 1000. Furthermore, different symbol energy-to-noise ratios (Es/N_0) were tested during training, and it was found that the optimal training Es/N_0 value was 7 dB. The validation dataset size used after training was 10,000, and the Es/N_0 value for validation was also set to 7 dB, as in the training phase.

As an example, the classical constellation for 16-QAM modulation and the constellations obtained using the autoencoder are shown in Figures 4 and 5, respectively. When these constellation sets are examined, it is observed that, unlike the symmetrical symbol placements in the classical 16-QAM constellation set, the two constellation sets derived using the autoencoder have an asymmetric structure, and all symbols have different energy levels. In the mapping diversity technique, the combined effect of the constellation sets used in two consecutive transmissions influences the bit/symbol error rate. Accordingly, the combined minimum Hamming distance of the two different sets used in mapping diversity, as shown in Fig. 5, is higher than the minimum Hamming distance of two consecutive standard 16-QAM constellation sets without mapping diversity.

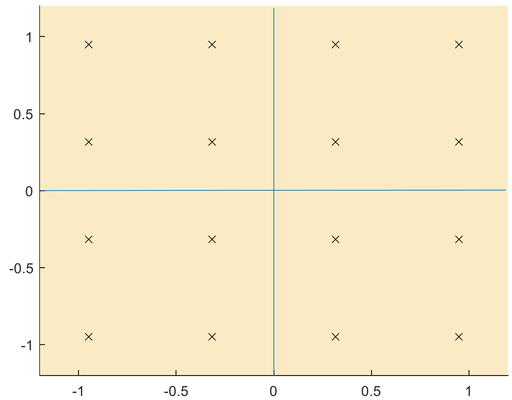
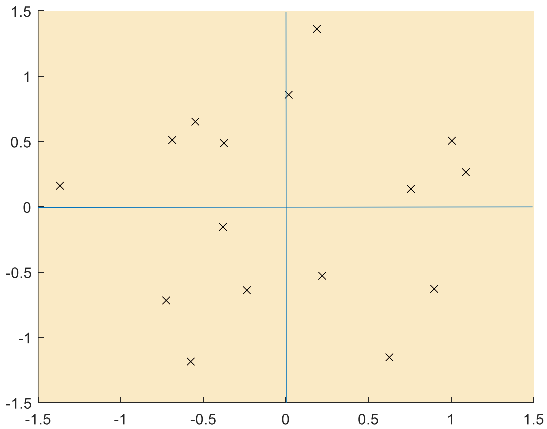


Figure 4. Classical constellation for 16-QAM



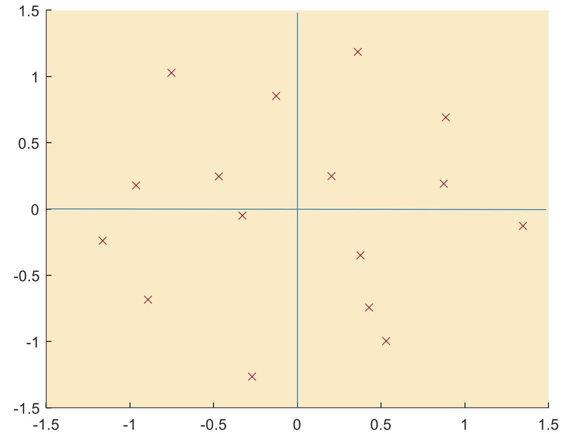


Figure 5. Constellations used in mapping diversity for 16-QAM

For 64-QAM modulation, another modulation type used in the simulations, the classical constellation set, and the constellation sets obtained using the autoencoder are shown in Figures 6 and 7, respectively. Similarly, it is observed that the constellation sets obtained using the autoencoder do not have a symmetrical structure, and all symbols have different energy levels. Simulations were conducted to evaluate the symbol error rate performance of the designed systems with respect to the Es/N_0 value. In the simulations, all channels were assumed to have Rayleigh flat fading. The channel fading coefficient was modeled as a complex Gaussian random variable with a mean value of zero and a variance of 0.5 per dimension. It was also assumed in all simulations that the receivers had perfect channel state information, meaning the channel coefficient values were known without error. The simulations were first conducted for the 8-PSK modulation technique, where each symbol consists of three bits, and the results are presented in Fig. 8. When the graphs in Figure 8 are examined, it is observed that the system designed with the mapping diversity technique using AE provides significant gains compared to the system without mapping diversity at all Es/N_0 levels. For instance, this gain is observed as 2 dB at a symbol error rate of 10^{-3}. An additional point to note here is that since the channel usage value is two in both systems, the diversity gain remains two regardless of whether mapping diversity is applied. The mapping diversity technique increases the minimum Hamming distance, and similar to coding gain, it reduces the symbol error rate.

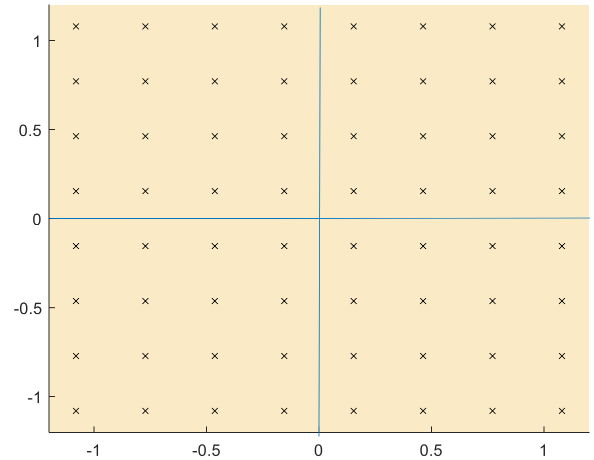


Figure 6. Classical constellation for 64-QAM

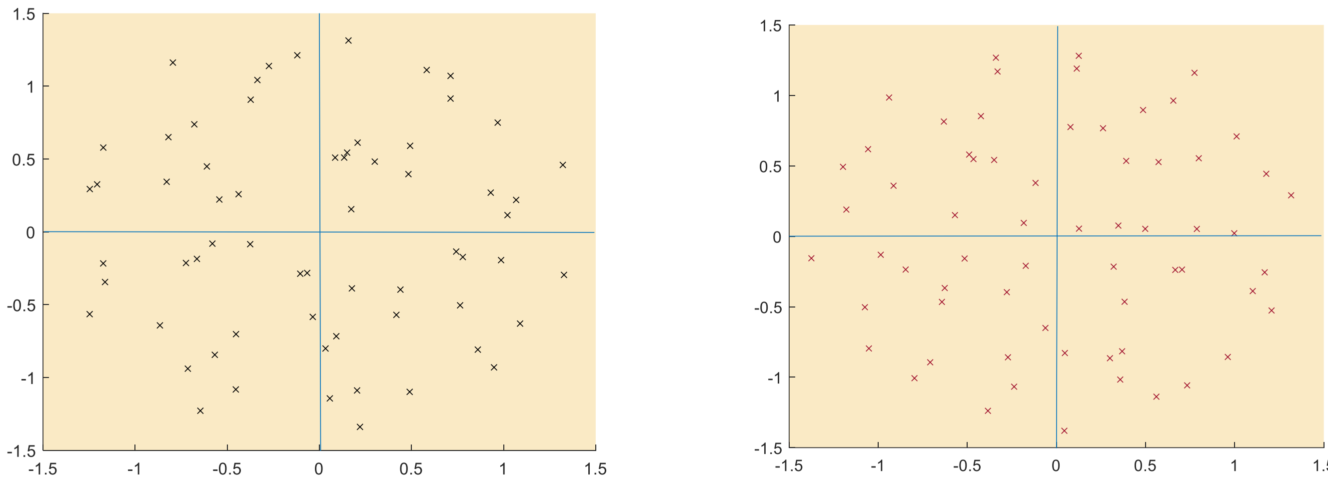


Figure 7. Constellations used in mapping diversity for 64-QAM

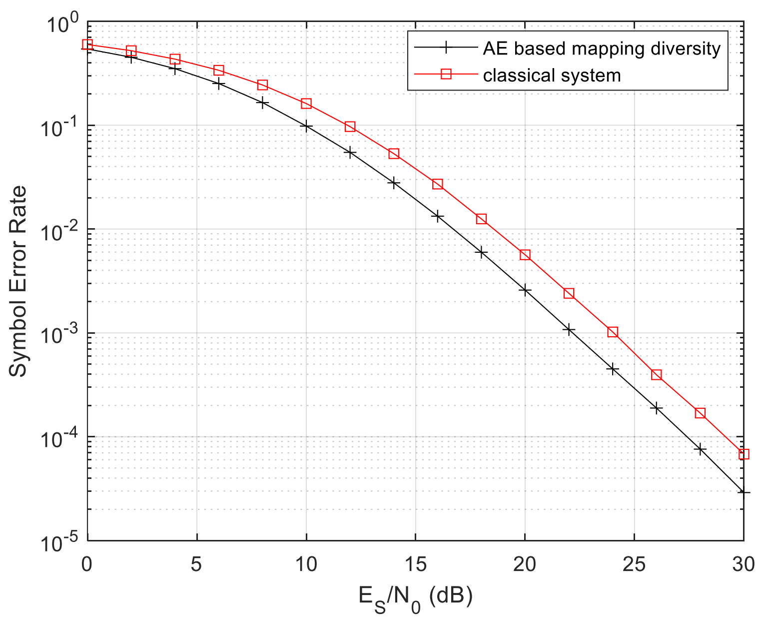


Figure 8. Simulation results for 8-PSK

Simulations were also conducted for the 16-QAM and 64-QAM modulation schemes, which have higher modulation levels. The results obtained for the 16-QAM modulation technique are presented in Fig. 9. Similarly, it is observed that the system designed with mapping diversity using AE provides better performance at all Es/N_0 levels compared to the case where mapping diversity is not applied. Specifically, for a symbol error rate of 10^{-3}, a gain of 2 dB is observed, similar to the results for 8-PSK modulation.

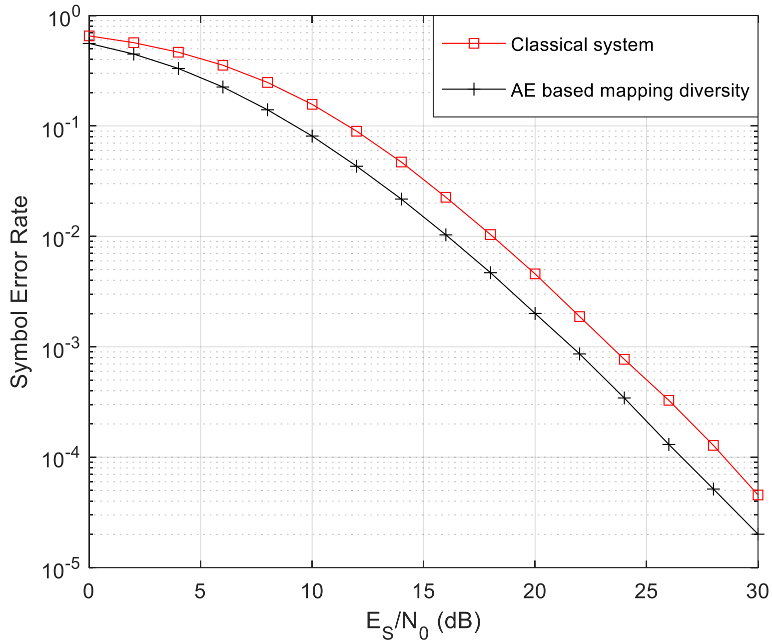


Figure 9. Simulation results for 16-QAM

Finally, all simulations were repeated for the 64-QAM modulation scheme, and the results are presented in Fig. 10. Similar to the previous simulations, it is observed that the system designed with mapping diversity using AE outperforms the system without mapping diversity. Specifically, for 64-QAM, an even higher performance improvement is observed compared to the previous two modulation techniques (8-PSK and 16-QAM), with a gain of 3 dB at a symbol error rate of 10^{-3}. Lastly, for a comprehensive comparison, the symbol error rates at different Es/N_0 levels for all three modulation schemes are numerically presented in Table 2.

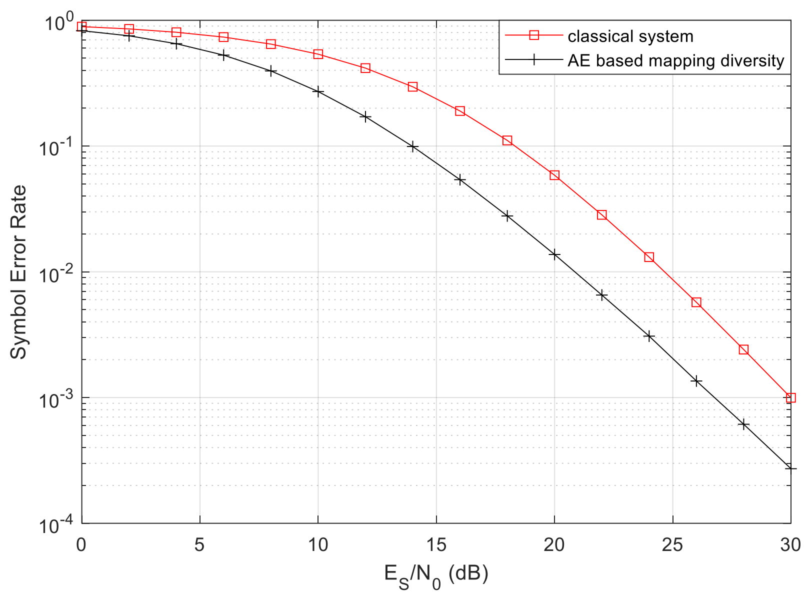


Figure 10. Simulation results for 64-QAM

Table 2. Symbol error rates at different Es/N_0 values according to modulation types.

(Es/N_0)	Modulation Type					
	8-PSK		16-QAM		64-QAM	
	Classical system	Deep learning based system	Classical system	Deep learning based system	Classical system	Deep learning based system
5 dB	0,38	0,30	0,41	0,28	0,74	0,55
10 dB	0,16	0,10	0,157	0,081	0,54	0,27
15 dB	0,04	0,02	0,035	0,015	0,23	0,07
20 dB	0,0057	0,0026	0,0046	0,002	0,058	0,013

4. Conclusion

Mapping diversity aims to correct erroneous information by transmitting multiple copies of the original data block, either identical or processed through certain operations. While the transmitted copies from the transmitter share the same modulation type and level, diversity gain is achieved by altering the positions of the signals within the constellation set. In this study, the classical mapping diversity method has been implemented using a deep learning-based design with an autoencoder. The performance of the designed system was evaluated under fading channel conditions for different modulation schemes and compared with the conventional repeated transmission method, which uses the same classical constellation set. According to the results, the autoencoder-based mapping diversity method provided significant gains over the conventional system without mapping diversity across all signal-to-noise ratio levels and modulation techniques. Notably, the gain was highest for 64-QAM modulation, where the modulation level is the highest.

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