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Assessing Wireless Communication Systems Performance Metrics Using Artificial Neural Networks: A Modelling and Simulation Approach

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ABSTRACT

In light of the increasing complexity associated with processing voluminous data, including signal, image, and video information, this study presents an approach to assess wireless communication system performance using artificial neural networks (ANNs). The focus is on key metrics such as mean square error (MSE), capacity, and error probability. ANNs, as intelligent tools, facilitate the analysis of these metrics via training and testing of data, employing backpropagation algorithms. Special attention is given to the evaluation of error probability related to signal transmission and reception, MSE for wireless channel coefficient estimation, and capacity for information transfer quantity relative to signal-to-noise ratio. These evaluations are executed in the matrix laboratory (MATLAB) environment. The findings suggest that the proposed ANN-based modelling and simulation method offers an excellent means for assessing wireless system metrics, along with existing research methodologies. The proposed approach is pertinent for the development of advanced wireless applications associated with 5G and 6G systems.

1. INTRODUCTION

Wireless communication systems are growing globally in a broader perspective due to demand in applications for 5G, 6G systems [1, 2] for faster information transfer of the order of gigabitspersecond (Gbps) or terabitspersecond (Tbps) between transmitter and receiver in a wireless link. Applications for audio, video, multimedia, need to be sent at the faster data rate for upcoming 6G systems [3] thereby requiring reduced probability of error, lesser mean square error (MSE) and information theoretic capacity requirements for the wireless channel. Further, wireless systems in the frequency ranges of the order of GigaHertz (GHz) and TeraHertz (THz) [4] present significant aforementioned challenges which needs to be addressed. Concatenation of multiantenna techniques as that of multiple input multiple output (MIMO), massive MIMO systems [5] in wireless domain are essential to increase the spectral efficiency, coverage, reliability and ultimately increase the data rate of wireless systems for catering multimedia applications. MIMO systems provide an increase in gain in terms of diversity with antenna selection [6] possibilities where diversity gain is the product of the antennas in the wireless transceiver chain. However, when it comes to an implementation perspective during realization of wireless communication systems, there arises specific problems in the form of research issues of determination of wireless channel coefficients, handling information bits in a wireless channel and data detection. To address aforementioned specific research problems intelligently, a precursor via methodologies such as artificial neural networks (ANN) for wireless communication [7] and wireless networks [8] can be a suitable tool. Artificial neural networks are a subsection of the field of machine learning [9] concepts which uses the intelligence in an artificial manner which basically comes from the concepts of neurons biologically. ANN is an arrangement of input layer of neurons, hidden layer of neurons and output layer of neurons where it uses learning [10] from the algorithms such as backpropagation (BP) [11]. The BP algorithm trains the neural network and creates a model with learning rate [12] for the specific application such as realization of wireless communication system. From the trained ANN it can be tested for finding the intended output from its intelligence knowledge acquired as a result of training which creates a simulation arrangement where it makes to do adaptation [13]. For assessing the wireless communication system metrics ANN can be a possible solution.

Literature works relating to artificial neural networks for wireless communication systems are presented in the studies [14-20]. Prediction of path loss in wireless communication systems using artificial neural networks is given by Wu et al. [14]. Deep learning based wireless communication system analysis is done in frequency selective channels for MIMO systems [15]. Performance evaluation of mobile adhoc networks (MANETs) in a qualitative prospect is given by Barki et al. [16] using artificial neural networks. Load user analysis is done by Abinoja et al. [17] with ANN technique using backpropagation algorithm and results were obtained in MATLAB. Channel estimation is done using deep learning techniques for wireless communication systems [18] as a statistical performance analysis with fact that deep learning uses additional layers which introduces complexity which is the major difference from artificial neural networks. Deep learning based channel state information analysis is done for 5G systems which uses orthogonal frequency division multiplexing (OFDM) scheme [19]. A testbed for analysis of multiantenna wireless application with ANN is presented in the study [20] where capacity analysis and probability of error are obtained for binary phase shift keying (BPSK) modulation scheme in Rayleigh fading channel conditions. Peak to average power ratio (PAPR) analysis of OFDM signals using ANN is presented in the research paper which provides useful insights relating to PAPR [21]. All the above-mentioned literature works give excellent results for ANN centric analysis of wireless communication systems in terms of finding pathloss, frequency selective channel analysis with deeplearning techniques, analysis in MANETs, load user analysis for ANN backpropagation and channel estimation with deep learning techniques are highly significant. Though the work of Priya et al. [20] provides capacity and probability of error analysis in Rayleigh fading. This research article will provide the three metrics of mean square error (MSE) for determination of wireless channel coefficients, capacity for handling information bits in a channel, probability of error for data detection all realized in an ANN system. This proposed research article is summarized clearly with concise that it provides mean square error analysis in different wireless channels, capacity analysis, probability of error in Rician fading channels, which makes it also significant hence exploring possible research results for supporting upcoming 5G and 6G wireless communication systems.

This research article is presented in various sections to support analysis. Section 1 portrays introduction aspects for modelling and simulation of wireless communication systems and literature works which are done. Section 2 deals with wireless communication system analysis in Rayleigh and Rician fading channels. Section 3 presents artificial neural networks with backpropagation algorithms. Section 4 graphically analyses the simulation results obtained using MATLAB platform with artificial neural networks for a modelled wireless communication system. Section 5 gives the conclusion and future scope directions.

2. WIRELESS COMMUNICATION SYSTEMS IN RAYLEIGH FADING AND RICIAN FADING

Consider a wireless communication system with a mobile station (MS) and a base station (BS)with single antenna terminals experiencing Rayleigh fading. At a particular time instant t, the mobile station transmits an information data symbol using QPSK modulation scheme, where an information data symbol comprises of two information bits the received signal is given as:

$$y_{ray}(t) = d_i(t)h_{ray} + n(t) \tag{1}$$

where, $d_i(t) = \sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)$; i=1, 2, 3, 4 following QPSK data symbols, E_s is energy of the symbol and T_s is symbol duration, Further h_{ray} is the Rayleigh fading channel given as $h_{ray} = \propto e^{j\theta}$; where α is amplitude component, θ is the phase component and $n(t)$ is additive white Gaussian noise(AWGN) with mean μ_x and variance σ_x^2.

Using the above mathematical terminologies, the received signal reaches to:

$$y_{ray}(t) = \sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right) \propto e^{j\theta} + n(t) \tag{2}$$

Likewise for a Rician fading channel the received signal model with single antenna terminal is given as:

$$y_{ric}(t) = d_i(t)h_{ric} + n(t) \tag{3}$$

where, Rician fading channel is given as $h_{ric} = \propto e^{j\theta} + h$; where $h=a+jb$ is a complex entity following Rician distribution which represents the line-of-sight (LOS) component. The Rician received signal model is represented as:

$$y_{ric}(t) = \sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right) \left(\propto e^{j\theta} + h\right) + \mathrm{n(t)} \tag{4}$$

$$y_{ric}(t) = \sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right) h_{ric} + n(t) \tag{5}$$

Based on the above received signal model the mean square error (MSE) for the wireless communication system can be obtained by using least squares (LS) approach. In LS based estimation of wireless channel coefficients consider the objective function:

$$O = \left(y_{ric}(t) - h_{ric}\sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)\right)^2 \tag{6}$$

By partially differentiating the above Eq. (6) with respect to channel coefficients h_{ric}:

$$\frac{\partial O}{\partial h_{ric}} = 2\left(y_{ric}(t) - \hat{h}_{ric}\sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)\right)\left(-\sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)\right) \tag{7}$$

Minimizing the squared value, and equating to zero, Further, it reaches to:

$$0 = 2\left(y_{ric}(t) - \hat{h}_{ric}\sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)\right)\left(-\sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)\right) \tag{8}$$

$$\frac{0}{\left(-\sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)\right)} = 2\left(y_{ric}(t) - \hat{h}_{ric}\sqrt{\frac{E_s}{T_S}}\,cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)\right) \tag{9}$$

$$0 = \left(y_{ric}(t) - \hat{h_{ric}} \sqrt{\frac{E_S}{T_S}} \cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right) \right) \quad (10)$$

$$\hat{h_{ric}} \sqrt{\frac{E_S}{T_S}} \cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right) = y_{ric}(t) \quad (11)$$

The least square (LS) estimated value is given as:

$$\hat{h_{ric}} = \frac{y_{ric}(t)}{\sqrt{\frac{E_S}{T_S}} \cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right)} \quad (12)$$

$$\hat{h_{ric}} = y_{ric}(t) \left(\sqrt{\frac{E_S}{T_S}} \cos\left(2\pi f_c t + (2i-1)\frac{\pi}{4}\right) \right)^{-1} \quad (13)$$

The mean square error (MSE) using LS algorithm for a wireless communication system is given as:

$$MSE = E[ee^H] \quad (14)$$

where, error $e = h - \hat{h_{ric}}$ and using in above (14) it results in mean square error for the wireless communication system when signal/pilot signal is transmitted from mobile station to base station:

$$MSE = E\left[(h - \hat{h_{ric}})(h - \hat{h_{ric}})^H \right] \quad (15)$$

Further, probability of error of wireless communication system experiencing Rayleigh fading channel for the received signal model in (1) can also be obtained as [22]:

$$P_{bQPSK} = \frac{1}{2}\left[1 - \frac{\sqrt{SNR}}{\sqrt{SNR+1}}\right] \quad (16)$$

Similarly, the capacity of wireless communication system in Rician fading channel can be obtained by considering the statistics as per [23, 24] as:

$$c_{ray} = max_{f_{d(d)}} \left| \frac{1}{2} log_2 \left(1 + h_{ray} \frac{S}{N}\right) \right| \quad (17)$$

3. ARTIFICIAL NEURAL NETWORKS FOR WIRELESS COMMUNICATION SYSTEMS

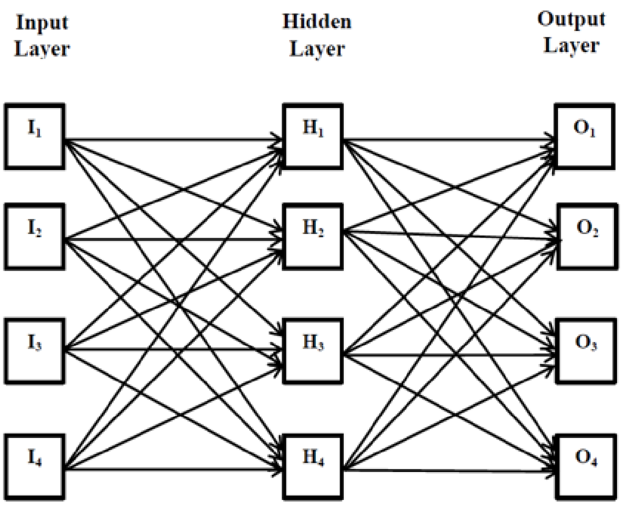

Figure 1. ANN modelling for assessment metrics of wireless communication systems

Artificial Neural Networks (ANN) are intelligent techniques based on Artificial Intelligence (AI) resembling biological neurons which have an input layer, hidden layer and an output layer as shown in Figure 1. The role of the input layer is to take the input values such as received signal values, signal energy, symbol duration and feedforwards it to the hidden layer which applies the activation function such as logsigmoidal function, tansigmoidal functions and forwards it to the output layer where the output is predicted as the wireless channel coefficients.

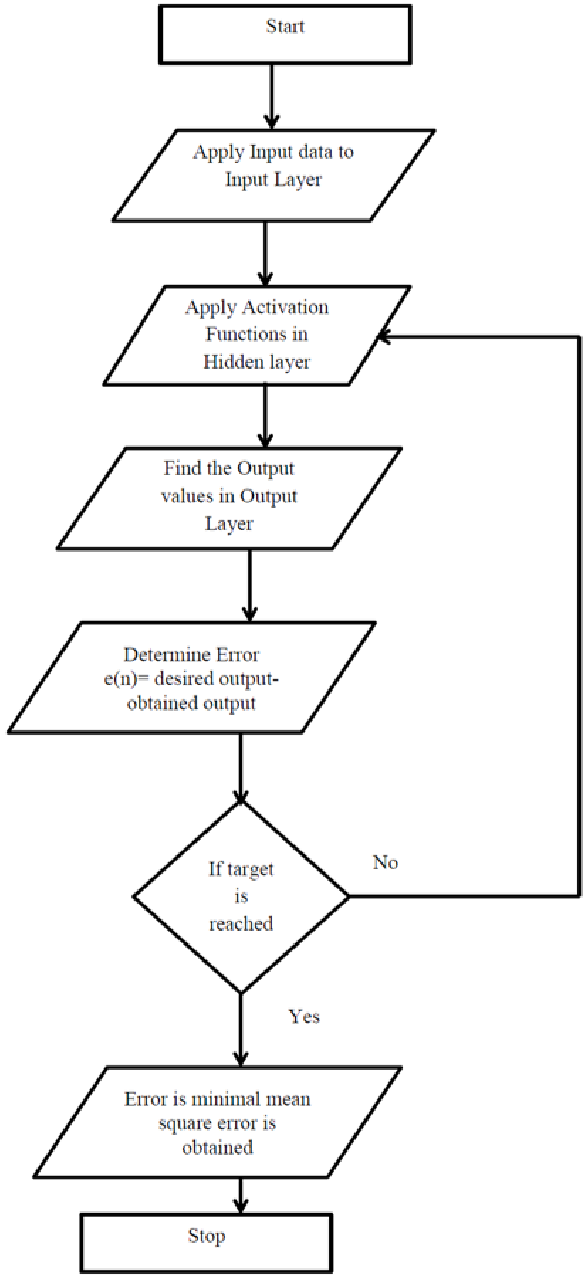

Figure 2. Flowchart of ANN for training assessment metrics of wireless communication system

The input layer, hidden layer and the output layer have N neurons in each of the layers and the ANN uses supervised or unsupervised learning with algorithms such as backpropagation (BP) algorithm. The backpropagation algorithm makes the weights and biases to update for each of the iterations as long as the target is reached. Moreover, it is a stochastic gradient method approach which makes the error to get reduced which implies to reducing the mean square error

(MSE) to a significant extent as per the learning rate, activation functions such as tansigmoid activation function, purelin activation which make it to undergo learning. The backpropagation algorithm weight update equation is given as:

$$w(presentweightneuron) = w(pastweightneuron) - \alpha_{rate}\frac{\delta o}{\delta w} \quad (18)$$

where, learning rate is a parameter considered to be in the range $0 \le \alpha_{rate} \le 1$. The mean square error obtained as a result of the number of iterations after convergence is found to be:

$$MSE = E[(error)]^2 \quad (19)$$

Further error=desiredoutput- actualoutput, is given as:

$$MSE = E[(desiredoutput - actualoutput)]^2 \quad (20)$$

Therefore, the created ANN which are feedforward networks pass the inputs in a sequential manner through hidden layer and finally to the output layer which will act as trained neural network. Training the ANN, with algorithms such as backpropagation can be depicted via the following flow chart as shown in Figure 2. From the trained neural network when tested with input values it can be used to provide the resultant output values for any application such as wireless communication systems performance assessment metrics probability of error, mean square error and capacity. The training functions for the ANN backpropagation algorithms are trainlm for levenberg marquardt algorithm, trainbfg for quasi newton backpropagation algorithm, trainscg for scaled conjugate gradient algorithm.

4. SIMULATION RESULTS AND DISCUSSIONS

This section provides modelling and simulation results in MATLAB for mean square error (MSE) capacity and probability of error of wireless communication system in Rayleigh fading and Rician fading channels with Artificial Neural Networks (ANN). Neural networks training tool in MATLAB gives the trained neural network feedforward network using backpropagation algorithm using training function trainbfg. Using montecarlo simulations, performance of quadrature phase shift keying (QPSK) for probability of error are analyzed.

Figure 3 shows the assessment metric of mean square error realized using trainbfg, for obtaining mean square error of wireless communication system. It takes 13 iterations to realize the target, which is the mean square error for the backpropagation algorithm using the training function. Likewise the other training functions trainlm, transcg are also be done using the training tool in MATLAB platform.

Similarly, Figure 4 shows the mean square error against signal to noise(S/N) ratio performance for a wireless communication system using least squares algorithm for various pilot sequence lengths. The pilot signal or the training signal is a unity vector sequence comprising of ones from which the wireless channel coefficients such as Rayleigh fading and Rician fading are obtained. When the number of pilots increases the mean square error also reduces for increasing signal to noise ratio. For instance, when 2 pilots are considered, it requires a S/N value of *9dB* for *MSE* of 10^{-2} and likewise when 16 pilots are used the S/N value is *5 dB* for the same MSE value under observation during simulation in MATLAB.

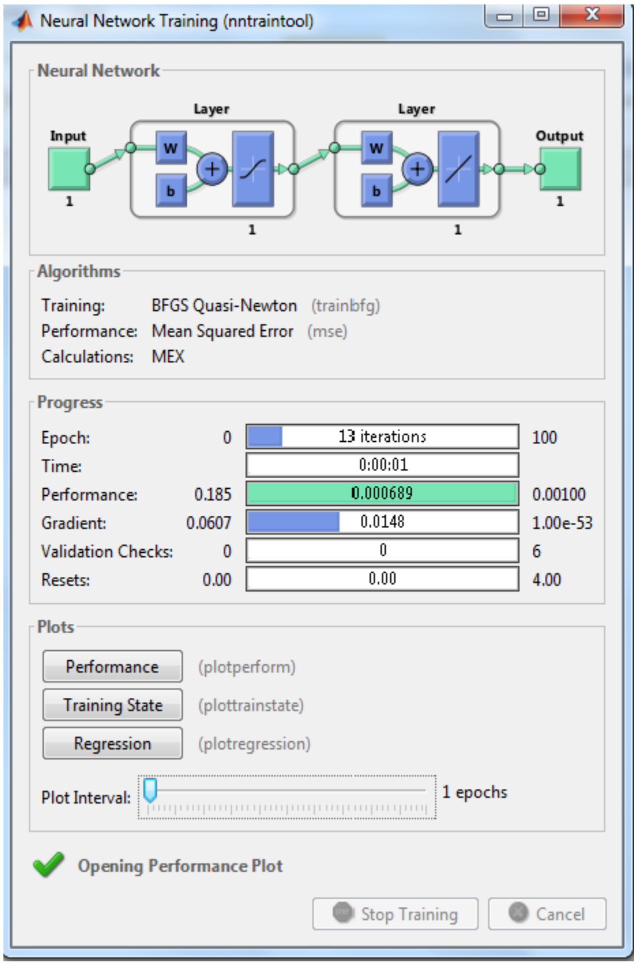

Figure 3. Artificial neural network realization of assessment metric of mean square error

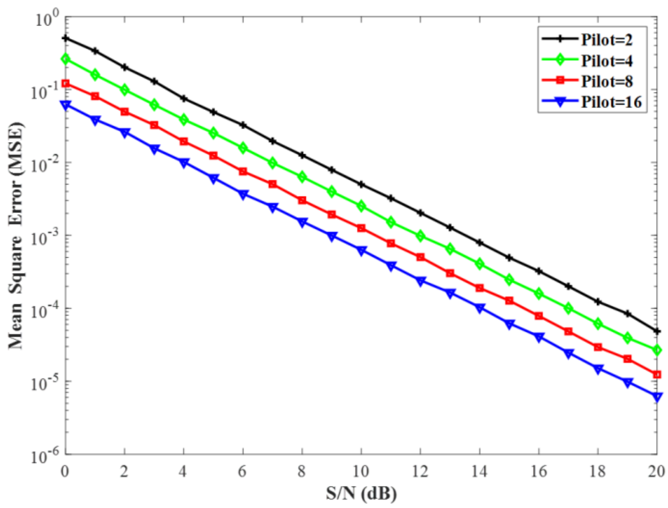

Figure 4. Mean square error vs S/N for pilot lengths using least squares (LS) algorithm

Figure 5 shows the training of neural network for capacity of wireless communication system, using trainbfg algorithm and its MSE analysis in reaching the target for 100 epochs is shown in Figure 6. The target converges as the number of iterations increases thereby creating a suitable trained network for prediction of assessment metric of capacity [23].

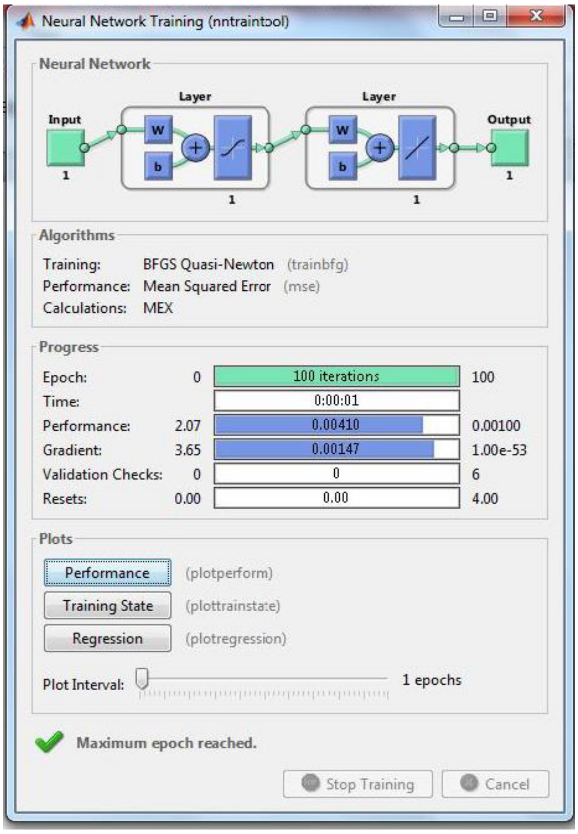

Figure 5. ANN training neural network using backpropagation algorithm for assessment metric capacity

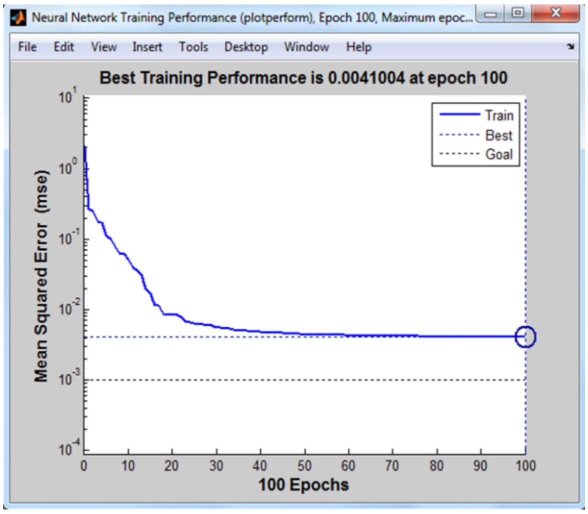

Figure 6. ANN mean square error using trainbfg for capacity analysis

Figure 7 shows the assessment metric of capacity against signal to noise (S/N) ratio in Rayleigh fading and Rician fading for an operating bandwidth of *1 GHz*. When signal to noise ratio of *10 dB* is considered for analysis, Rayleigh fading results in capacity of 1.7×10^9 bits/sec/Hz. Further for Rician fading for same S/N value of 10 *dB* capacity [24] is 3.9×10^9 bits/sec/Hz when the Rician fading component value is *1 dB* and increases gradually to 5.9×10^9 bits/sec/Hz when Rician fading component is *4 dB*. The obtained results can be used for analysis of wireless communication systems to carry out beamforming [25] in cellular networks, heterogeneous networks [26] for radio resource allocation [27] in present day 5G and upcoming 6G systems.

Figure 8 shows the ANN model to obtain probability of error and Figure 9 shows the probability of error in Rayleigh fading and Rician fading for QPSK modulation scheme. To obtain a probability of error of 10^{-2}, Rayleigh fading takes *17* dB and Rician fading takes *15 dB* and lesser than that when the Rician fading component increases from *1 dB* onwards. Since QPSK modulation scheme uses two bits as symbols for transmission of data from mobile station to base station the probability of error reduces significantly. Rician fading scheme provides better performance in comparison to Rayleigh fading for QPSK digital modulation scheme. From the results the findings and implications give a possibility where a wireless communication system metric can be obtained with training and testing of ANN.

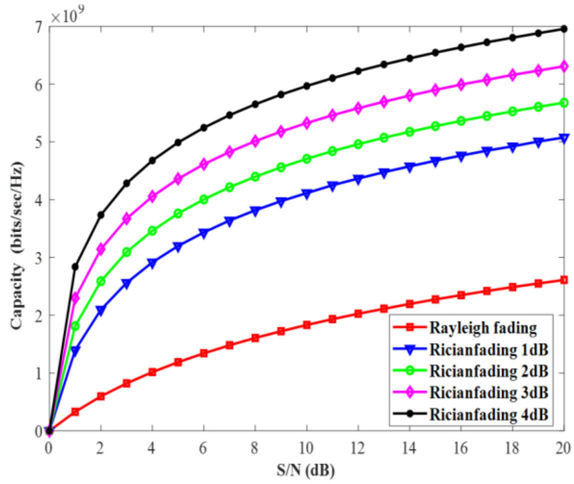

Figure 7. Capacity vs S/N (dB) for Rayleigh fading and Rician fading

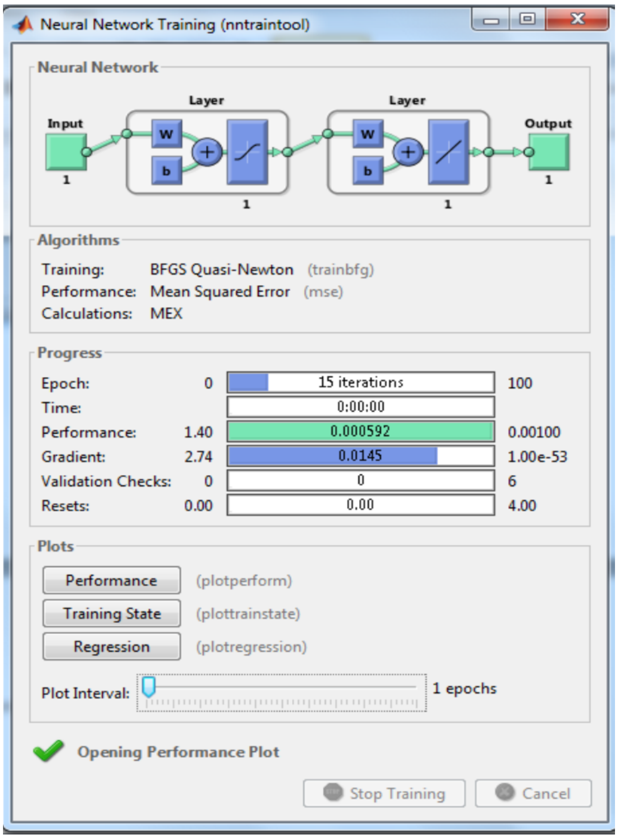

Figure 8. Artificial neural network model of assessment metric probability of error using QPSK

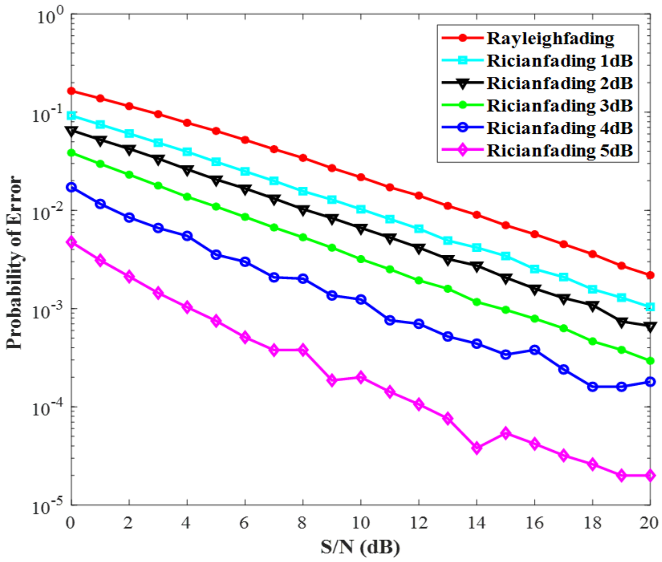

Figure 9. QPSK Probability of error in Rayleigh fading and Rician fading using artificial neural networks

5. CONCLUSIONS

This research article gives conclusions from the key findings for modelling and simulation of wireless communication assessment metrics of mean square error, probability of error and capacity of wireless communication systems using artificial neural networks technique. Analysis is done against signal to noise ratio value for Rayleigh fading and Rician fading channels. ANN backpropagation algorithms are used to train the wireless systems for the assessment metrics for convergence based on the iterations epochs for obtaining the target values. From the trained ANN model the assessment metrics can be obtained when tested with the required values in simulation. As future work and scope intelligent techniques such as deeplearning based neural networks such as recurrent neural networks and convolutional neural networks can be considered for further analysis to support 5G and 6G wireless communication systems.

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