Digital Modulation Augmentations with Adaptive Modulation and Coding and AI in Cellular Networks.

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ABSTRACT

A user closer to a base station can operate using a higher order of quadrature modulation, such as 64-QAM, for its communication link, however once the channel's condition vary such as distance or noise, the throughput and spectral efficiency drops and results in unreliable and inefficient link. The study aimed to implement digital modulation techniques, for efficient data transmission in cellular networks. So the efficacy of Adaptive Modulation and Coding (AMC) and the prospect of Artificial Intelligence (AI) were considered as solution. Simulation was carried out in MATLAB R2025a and compared the performance of the various digital modulation techniques in their SNR and BER characteristics, in presence of Additive White Gaussian Noise. Also adaptive modulation and deep learning were applied to ascertain their effectiveness. The results showed that AMC augmented approaches gave the best BER/SNR performances, followed by M-QAM, QPSK, and BPSK in that order under fixed SNR situations. The use of Convolution Neural Network (CNN) gave 100% prediction for BPSK, 95% for QPSK, 90% for 16-QAM and 85% for the 64-QAM. So the confusion matrix favoured all the modulation schemes and mostly the lower order ones.

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1. INTRODUCTION

The importance of the internet in our today's world to man and our day-to-day activities is ever growing, giving rise to the need for better performance metrics for data-rate, spectral efficiency, coding and error-correction efficiency in the system, being mainly built on the technology of digital modulation schemes such as BPSK, QPSK, and QAM, adaptive modulation and coding (AMC), and their applications in the cellular networks of the scope of the broader boundary of the internet. The challenges of time-variant channel conditions, noise and interference, and their resolution in the intermediary adaptive modulation and coding schemes (AMC), and the further necessities of more accurate channel state information (CSI), and efficiency of error-correction and feedback systems culminated to prospective augmentation techniques for digital modulation systems using artificial intelligence, such as modulation schemes classification using convolution neural networks (CNN), adaptive modulation recognition using deep learning etcetera. In modulation, parameters of a baseband signal (baseband) such as amplitude, phase, frequency, are modified, so as to encode in it, information, making it a message signal (bandpass) of usually a higher frequency compared to the original, to be transmitted from one point to another. Modulation also requires demodulation at the receiver's end, where the baseband signal is obtained for use [1].

In digital modulation, a digital bit stream is transmitted by altering parameters of analog carrier signal, thereby using discrete signals to vary time-varying signals' parameters, in what is refered to as the concept of shift keying. Popular with digital modulation, and depending on the parameters being varied we could either have Frequency Shift Keying (FSK), Amplitude Shift Keying(ASK),or Phase Shift Keying (PSK) of which BPSK, QPSK are based, or QAM a combination of Amplitude Shift Keying And Phase Shift Keying [2].

In wireless communication networks, there is a demand for high data rate, spectral efficiency and coverage reliability, which is ever growing. However, the performance of wireless links suffer the effects of channel fading, addition of noise and interference, which affects the total throughputs of data transmissions. In order to achieve high reliability, the transmission rate can be reduced, but this would result into a low data rate, which is undesirable, therefore to improve the system, the transmitted signal in the face of fading, path loss, and noise, is modified through a process of link adaptation or adaptive modulation. In this the modulation and coding scheme (MCS) is adapted to the channel states conditions to achieve the best performance characteristics at all times - when a node is closer to the base station, a higher modulation order 64-QAM with high code rate is assigned, while 16-QAM is assigned as the user is far from the base station. Higher orders of modulation can allow more bits to be sent per symbol, and hence higher throughputs or spectral efficiencies, however when using 64-QAM, high signal-to-noise ratios (SNRs) are required to overcome interference and maintain a bit error rate [1].
However in this paper, a consensus is drawn from the original fixed modulation schemes through the upgrades of adaptive modulation and coding, and has evolved toward an augmentation in the applications of link adaptation or AMC, necessitated by challenges such as inaccurate channel state information, error recognition and correction inefficiency, resulting in latency, and low data-rates; so therefore the invent of artificial intelligence in digital modulation. The potential of convolutional neural networks as a technique of artificial intelligence expressed by [3] was exemplified in a final experiment, fore-lighting the prospect of this frontier in achieving momentous strides in achieving optimal data-rate. Before, now the adaption of higher order but fixed modulation schemes had been the norm in digital broadband communications for better throughputs and efficiency but this study has implemented the AMC a system that toggles among the modulation schemes and adapts the one most suited for optimal signal transmission. it adapts a higher modulation scheme when it senses improvement in channel condition. The study also demonstrated the prospect of AI in optimizing performance using the confusion matrix an effort in a new frontier in communication engineering. The objectives of the study include to simulated the traditional fixed modulation schemes: BPSK, QPSK, and QAM, showing their constellation and their performances using BER and SNR in the AWGN channel. Secondly, to implement an AMC scheme and demonstrate its application in optimizing wireless communication. Furthermore, to demonstrate the application of CNN was also found to be a viable tool in effective use of modulation and coding schemes.

2. THEORETICAL ANALYSIS

In this section, the concepts of digital modulation, Adaptive Modulation and Coding (AMC),ArtificialIntellligence(AI) and Cellular Networks will be discused as within the scope of this study.

2.1. Didital Modulation

Digital modulation is the process of impressing the data to be transmitted onto the radio carrier for the purpose of spectral efficiency [4]. In this study, the Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK) and Quadrature Amplitude Modulation (QAM) were considered. BPSK is the simplest form of PSK, it's also known as 2-PSK. It uses two phases 0 and π separated by 180°. It can modulate at 1 bit per symbol, and so it is not suitable for high data rate applications and it is equivalent to 2-QAM [1]. QPSK, Quadriphase-PSK, 4-PSK, or 4-QAM has 4 phases and constellation points all separated by 90°, and it can encode 2 bits per symbol, and hence can transmit twice the data rate as compared to BPSK in a given bandwidth [1]. QAM is a combination of amplitude and phase modulation. The major advantage of the QAM is the higher constellation points and bits per symbols that can be transmitted. The disadvantage is that the higher the constellation points the closer together they are, and consequently more susceptibility to noise [5]. As a result, higher order QAM, are used with adequately high signal-to-noise ratios SNRs [1]. The M-PSK signal model given in [6] is shown in Equation 1. And for M-QAM the transmitted signal representation in discrete form is contained in [7] as shown in Equation 2.

$$s_k(t) = \sqrt{\frac{2E_s}{T_s}}\cos(2\pi f_c t + \frac{2\pi k}{M}) \quad (1)$$

Where S_k (t) is the transmitted signal for the kth symbol, E is energy per symbol, T is the symbol duration and M, the constellation points.

$$s_k(t) = \sqrt{\frac{2E_s}{T_s}}\left[a_k \cos(2\pi f_c t) - b_k \sin(2\pi f_c t)\right] \tag{2}$$

Where a_k and b_k are amplitude levels for in-phase and quadrature phase components, and f_c, the carrier frequency.

2.1. Adaptive modulation and coding (AMC)

A link-adaption technique, which has the ability to choose the best method for modulation with respect to the channel condition to maintain high performance at all times and sustain the continuous connectivity, especially with varying-channel conditions [8][9]. The wireless transmitter changes the modulation scheme e.g the QPSK,16-QAM, 64-QAM, 256-QAM and the coding rate e.g. 1/2, 2/3, 3/4, 5/6 in line with the quality of the existing wireless channel. The method provides various modulation scheme and modulation levels according to instantaneous channel conditions such that: when the received signal is not faded, the modulation mode that has higher data rate is selected to take advantages of good channel conditions and maximize throughput. And when the received signal fades, the modulation level that decreases a data rate is selected [10]. The channel quality is usually measured by the signal to noise ratio, bit error rate or channel quality indicator (CQI) [11].

2.2. Artificial Intelligence (AI)

AI based modulation and coding scheme does not classify the channel, it learns the modulation and coding scheme MCS that maximizes throughput while penalizing transmission errors [12]. The Convolution Neural Network (CNN) learns the baseband samples and infers the attributed channel characteristics thereby outputting the channel quality-class such as Poor, Good, Excellent. CNN approach is suited for automatic modulation classification due to their ability to learn discriminatory features of signal data [13]. With this information, it will estimate the modulation scheme of any newly received signal [13]. This can be actualized using the confusion matrix where the learned MCS is mapped onto the signal bit stream for the purpose of accuracy [14].

2.3. Wireless Communication

Wireless network viability has become user-centric expressed in the satisfaction derived the user [15]. The communication system supports mobile telephony, internet access, monitoring systems, and digital services[16]. The study was carried out in a 4G wireless environment where the mobile phones or devices connect to the base station through a wireless channel with the aid of electromagnetic waves. The wireless transmission chain comprises of the data, channel coding, and modulation. The wireless channel is characterized by noise, fading and interference and the AMC and AI can scan the received signal and help to determine the appropriate modulation and coding scheme.

2.2. Signal-to-Noise Ratio (SNR) and Bit Error Rate

SNR is defined as the signal power divided by the noise power and it is the ratio of the signal power to the noise power in a communication link, it's expressed in decibel (dB), mathematically expressed as SNR =10log (signal power/noise power)dB [11]. Energy bit per noise ratio (Eb/No): Eb/N0 (the energy per bit to noise power spectral density ratio) is a specific signal-to-noise ratio (SNR) measure, usually applied in digital communication. It's also known as the "SNR per bit" [11].
Bit Error Rate (BER): The bit error rate or ratio (BER) is the ratio of the bit errors (E_b) and the total number of bits transferred (N_0) at a particular time interval. BER is unit less and can be represented as a percentage, e.g a BER of 10^{-4} means 1 error in every 10000 bits [11]. For the different modulation schemes, the bit error rate are expressed on Additive White Gaussian noise channel as contained in [17], and shown in Table 1.

Table 1. BER expressions on AWGN channel

Modulation	BER
BPSK	$Q(\sqrt{\frac{2E_b}{N_0}})$
QPSK	$Q(\sqrt{\frac{2E_b}{N_0}})$
M-QAM	$\frac{2}{log_2 M}$Q($\sqrt{\frac{2E_b}{N_0} log_2 M sin\frac{\pi}{M}}$)

2.3. Additive White Gaussian Noise (AWGN)

The term additive implies noise added to the signal from an external source, and affects the overall rate of information transmission, Gaussian meaning a noise that follows a normal distribution, while "white" is just as with white light, it describes a noise that contains equal amounts of all frequencies, i.e. a constant power spectral density across all frequencies, e.g. thermal noise is an AWGN [11]. Its probability density function is expressed in Equation 3.

$$p(n) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{r^2}{2\sigma^2}}) \quad (3)$$

Where, r = random value of noise

3. METHOD

This section involve four experiments, first to run a MATLAB script on the MATLAB R2025a application, for BPSK, QPSK, and 16-QAM, showing their constellation plots, and second to run another script that simulates BPSK, QPSK, 16-QAM, and 64-QAM, with results showing the plots of their BER vs SNR curves. Third, to implement the AMC and lastly, to train the Convolution Neural Network (CNN).

3.1. MATLAB script for the constellation plots of digital modulation techniques

The MATLAB script was entered to simulate BPSK, QPSK, and 16-QAM modulation and plot constellation diagrams for each modulation scheme. Random binary bit stream was generated as base band signal. The developed script is:

```
% Define parameters
M = [2 4 16];  % Number of symbols (2 for BPSK, 4 for QPSK, 16 for 16QAM)
N = 1000;  % Number of symbols

% BPSK Modulation
bpsk_symbols = 2*randi([0 1], N, 1) - 1;
bpsk_modulated = bpsk_symbols;
% QPSK Modulation
qpsk_symbols = randi([0 3], N, 1);
qpsk_modulated = pskmod(qpsk_symbols, 4, pi/4);

% 16QAM Modulation
qam_symbols = randi([0 15], N, 1);
qam_modulated = qammod(qam_symbols, 16);

% Plot constellation diagrams
figure;

subplot(3,1,1);
plot(real(bpsk_modulated), imag(bpsk_modulated), 'r.');
title('BPSK Constellation');

subplot(3,1,2);
plot(real(qpsk_modulated), imag(qpsk_modulated), 'r.');
title('QPSK Constellation');

subplot(3,1,3);
plot(real(qam_modulated), imag(qam_modulated), 'r.');
title('16QAM Constellation');
```

3.2. To run a script to simulate the BER and SNR performances of BPSK, QPSK, 16-QAM, and 64-QAM in AWGN channel

The MATLAB code was entered into the command window to simulate BPSK, QPSK, 16-QAM, and 64-QAM with respect to BER and SNR. The developed script is:

```
% Parameters
SNR_range = 0:2:20; % SNR range in dB
num_symbols = 100000; % Number of symbols to simulate
```

```
% Initialize BER results
BER_BPSK = zeros(length(SNR_range), 1);
BER_QPSK = zeros(length(SNR_range), 1);
BER_16QAM = zeros(length(SNR_range), 1);
BER_64QAM = zeros(length(SNR_range), 1);

% Simulate BPSK
for i = 1:length(SNR_range)
   SNR = SNR_range(i);
   data = randi([0 1], num_symbols, 1);
mod_data = 2*data - 1; % BPSK modulation
noisy_data = awgn(mod_data, SNR, 'measured');
demod_data = (noisy_data> 0);
   BER_BPSK(i) = sum(data ~= demod_data)/num_symbols;
end

% Simulate QPSK
for i = 1:length(SNR_range)
   SNR = SNR_range(i);
   data = randi([0 3], num_symbols, 1);
mod_data = pskmod(data, 4); % QPSK modulation
noisy_data = awgn(mod_data, SNR, 'measured');
demod_data = pskdemod(noisy_data, 4);
   BER_QPSK(i) = sum(data ~= demod_data)/num_symbols;
end

% Simulate 16-QAM
for i = 1:length(SNR_range)
   SNR = SNR_range(i);
   data = randi([0 15], num_symbols, 1);
mod_data = qammod(data, 16); % 16-QAM modulation
noisy_data = aw
Zgn(mod_data, SNR, 'measured');
demod_data = qamdemod(noisy_data, 16);
   BER_16QAM(i) = sum(data ~= demod_data)/num_symbols;
end

% Simulate 64-QAM
for i = 1:length(SNR_range)
   SNR = SNR_range(i);
   data = randi([0 63], num_symbols, 1);
mod_data = qammod(data, 64); % 64-QAM modulation
noisy_data = awgn(mod_data, SNR, 'measured');
demod_data = qamdemod(noisy_data, 64);
   BER_64QAM(i) = sum(data ~= demod_data)/num_symbols;
end

% Plot results
figure;
semilogy(SNR_range, BER_BPSK, 'b*-', SNR_range, BER_QPSK, 'ro-', SNR_range, BER_16QAM, 'gs-',
SNR_range, BER_64QAM, 'k--');
xlabel('SNR (dB)');
ylabel('BER');
legend('BPSK', 'QPSK', '16-QAM', '64-QAM');
grid on;
```

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3.3. Implementation of Adaptive Modulation and Coding (AMC) Modulation

In this experiment an Adaptive modulation and coding scheme which has the capability of changing between BPSK, QPSK, and 16-QAM was simulated and the results of BER vs SNR compared with the results of a scenario of an application of a single/fixed modulation scheme, being BPSK. The code was entered to simulate and compare adaptive modulation and coding with BPSK modulation, with a plot showing each of their BER vs SNR results.

```
% Parameters
SNR_range = 0:2:20; % SNR range in dB
num_symbols = 100000; % Number of symbols to simulate

% Initialize BER results
BER_BPSK = zeros(length(SNR_range), 1);
BER_adaptive = zeros(length(SNR_range), 1);

% Simulate BPSK
for i = 1:length(SNR_range)
    SNR = SNR_range(i);
    data = randi([0 1], num_symbols, 1);
mod_data = 2*data - 1; % BPSK modulation
noisy_data = awgn(mod_data, SNR, 'measured');
demod_data = (noisy_data> 0);
    BER_BPSK(i) = sum(data ~= demod_data)/num_symbols;
end

% Simulate adaptive modulation and coding
mod_schemes = {'BPSK', 'QPSK', '16-QAM'};
mod_orders = [2, 4, 16];
code_rates = [1/2, 2/3, 3/4];
for i = 1:length(SNR_range)
    SNR = SNR_range(i);

    % Adaptive modulation selection based on SNR
    if SNR < 5
mod_scheme = 'BPSK';
mod_order = 2;
code_rate = 1/2;
    elseif SNR >= 5 && SNR < 10
mod_scheme = 'QPSK';
mod_order = 4;
code_rate = 2/3;
    else
mod_scheme = '16-QAM';
mod_order = 16;
code_rate = 3/4;
    end

    % Generate random symbols
    data = randi([0 mod_order-1], num_symbols, 1);

    % Modulate
    if strcmp(mod_scheme, 'BPSK')
mod_data = 2*(data > 0) - 1;
    elseif strcmp(mod_scheme, 'QPSK')
mod_data = pskmod(data, 4);
    elseif strcmp(mod_scheme, '16-QAM')
mod_data = qammod(data, 16);
    end
```

```
    % Add AWGN
noisy_data = awgn(mod_data, SNR, 'measured');

    % Demodulate
    if strcmp(mod_scheme, 'BPSK')
demod_data = (noisy_data> 0);
        data = (data > 0);
    elseif strcmp(mod_scheme, 'QPSK')
demod_data = pskdemod(noisy_data, 4);
    elseif strcmp(mod_scheme, '16-QAM')
demod_data = qamdemod(noisy_data, 16);
    end

    % Calculate BER
BER_adaptive(i) = sum(data ~= demod_data)/num_symbols;
end

% Plot results
figure;
semilogy(SNR_range, BER_BPSK, 'b*-', SNR_range, BER_adaptive, 'ro-');
xlabel('SNR (dB)');
ylabel('BER');
legend('BPSK', 'Adaptive Modulation and Coding');
grid on;
```

3.4. Implementation of AI for the Modulation and Coding Schemes

This section involves a single experiment, that is, "Modulation Classification with Deep Learning". This experiment shows the use of a convolutional neural network (CNN), for modulation classification. Firstly, synthetic waveforms are generated, as training data for a CNN, for modulation classification, and the trained model is tested, using generated random waveforms. In this experiment the trained CNN recognizes the following modulation types, the first eight are digital and the last three are analogue: Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK), 8-ary Phase Shift Keying (8-PSK), 16-ary Quadrature Amplitude Modulation (16-QAM), 64-ary Quadrature Amplitude Modulation (64-QAM), 4-ary Pulse Amplitude Modulation (PAM4), Gaussian Frequency Shift Keying (GFSK), Continuous Phase Frequency Shift Keying (CPFSK), Broadcast FM (B-FM), Double Sideband Amplitude Modulation (DSB-AM), Single Sideband Amplitude Modulation (SSB-AM). Procedures includes:

3.4.1. Generation of the waveform for training

A loop was created that generates frames for each modulation scheme and these frames were saved with their respective labels in MAT files, to avoid the need to generate the data every time this syntax is run (A random number of samples were removed from the beginning of every frame to ensure all the starting points of the frames are random, with respect to the system boundaries and also to remove transients). This frames of the generated waveforms are shown in Figure 2 below.

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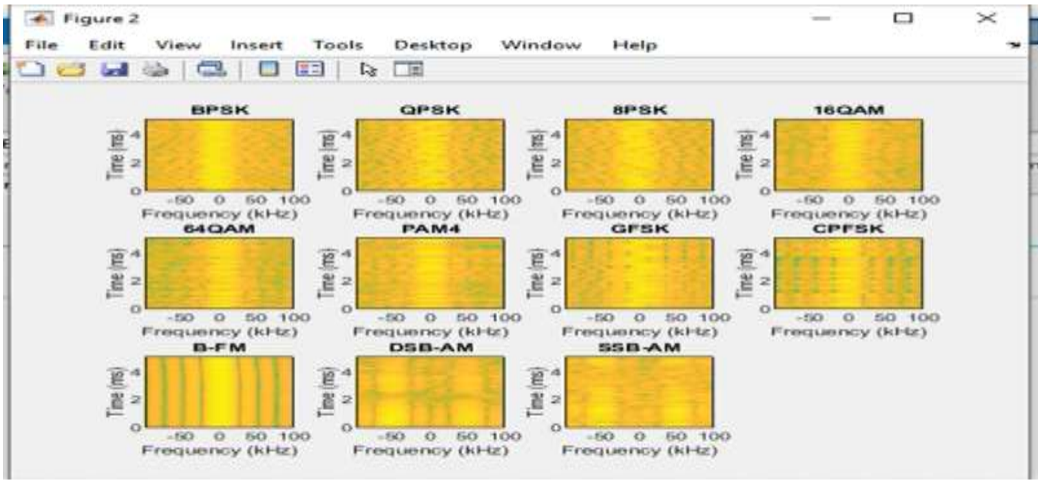

Figure 2: A spectrogram showing the frames of the generated waveforms used in training the CNN

3.4.2. Training the CNN and testing

It's either the network is trained or an already trained network is used, and for this experiment an already trained network was used. The trained network was evaluated by obtaining the classification accuracy for the test frames. And the confusion matrix for the test frames was the parameter used for testing the predictive classification performance of the CNN.

4. RESULTS AND DISCUSSION

The following are the results from the simulation experimental procedures and the respective discussions on them. It begins with the constellation plots of the modulation schemes as shown in Figure 3 and discussed afterwards.

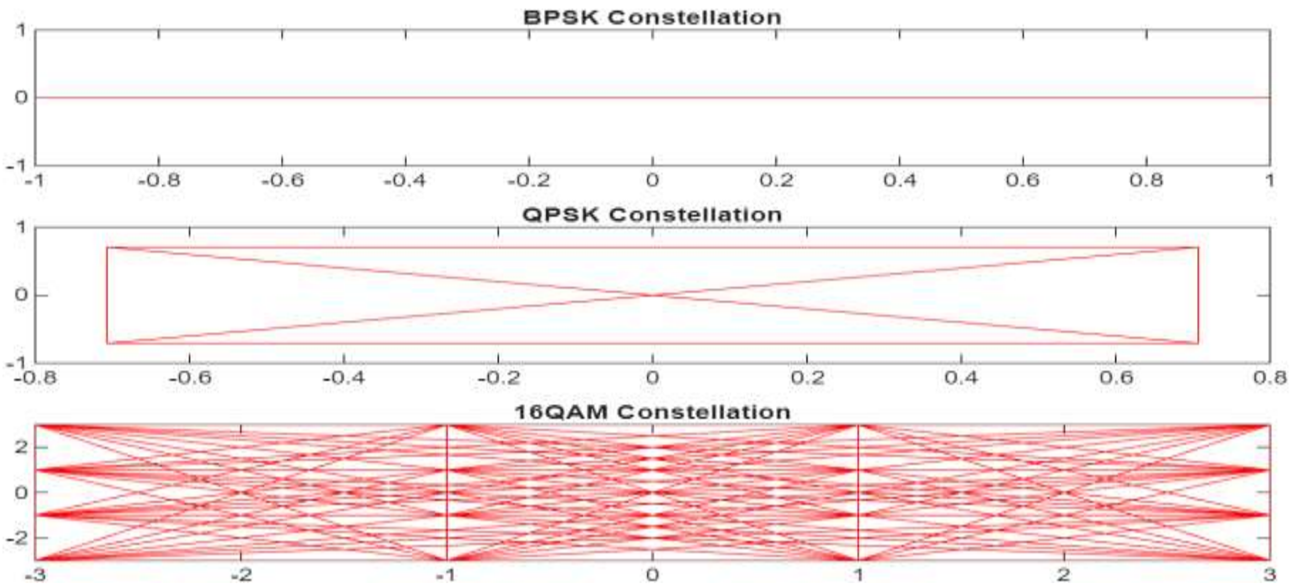

Figure 3: Constellation plots for BPSK, QPSK, and 16-QAM

The obtained constellation diagram plots shown in Figure 3 helped to represent the orientation and the number of bits transferable per symbol and the corresponding data rate of each digital modulation schemes. BPSK has two points on the real axis, representing binary digits 0 and 1, while QPSK has four points in the complex plane, representing two binary digits, and 16QAM has 16 points in the complex plane, representing four binary digits. This result shows the orientations, indicating the different phase positions and the corresponding bit code it transmits per symbol, for each modulation scheme, which are the constellation points of modulation schemes. This implies that more data bits can be transmitted per symbol for higher order modulation schemes like 16-QAM, and lesser for lower order modulation schemes e.g. BPSK, and the result of this is higher data transmission rate for higher order modulation schemes, but with the downside of high tendency of interference and errors, because of the little spatial differences between constellation points, but that can be controlled by error detection and correction schemes.

4.1. BER And SNR Performance of BPSK, QPSK, 16-QAM, and 64-QAM In AWGN Channel

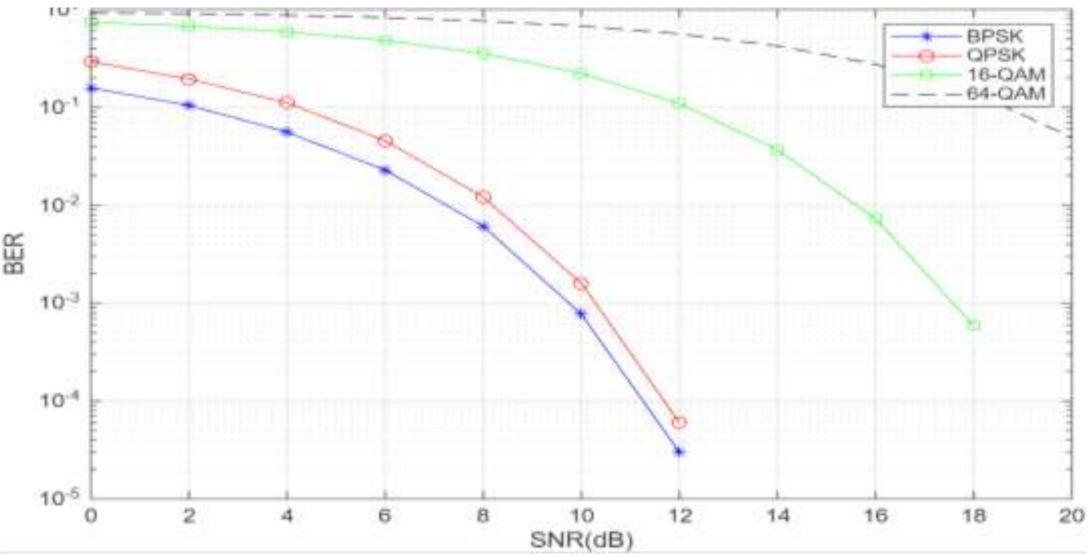

Figure 4: The BER versus SNR performance plots in AWGN

Figure 4 shows the different performance characteristics of the simulated modulation schemes. BPSK and QPSK required lesser signal power to attain a BER of zero, compared to the higher order modulation schemes, however in AWGN the system shows to be of optimal performance with 16-QAM and 64-QAM, as BPSK, and QPSK suffers the probability of signal degradation. Furthermore, the higher constellation points and code rate of the higher order modulation schemes resulted in higher data rate in transmission and tolerance to increased number of users in the system. The BER vs SNR curves show the relationship between the error characteristics and spectral performance of the modulation scheme being analyzed, and the results from this experiment alludes to the preference of higher order modulation schemes for systems requiring high data rate and multiple nodes of users, and the lower order modulation schemes e.g. BPSK for applications where robustness and lower bit-to-error rate and signal-to-noise ratio is required.

4.2. Results of AMC Application

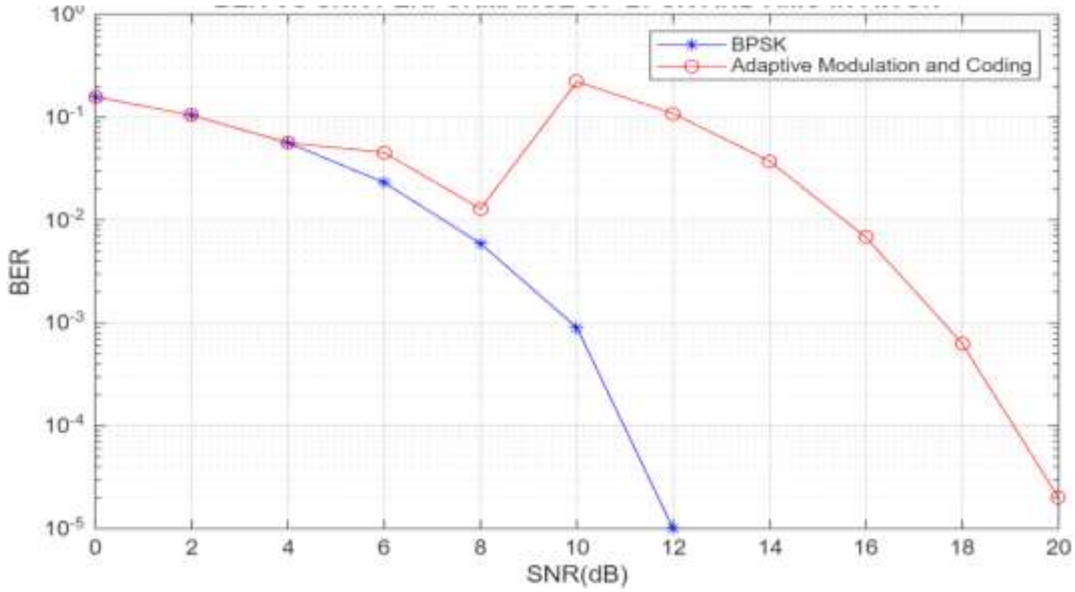

Figure 5: A plot showing BER vs SNR performance of BPSK and AMC in AWGN.

The BER versus SNR curves of both modulation schemes; namely the BPSK being a fixed modulation point of reference, and the adaptive modulation and coding scheme (AMC), represents their respective performance characteristics. The BPSK curve had the downward trend of decreasing BER with increase in SNR and also the AMC until the signal level of 4dB, where the modulation scheme was switched to QPSK, and at 8dB it switched again to the 16-QAM modulation scheme in response to the AWGN channel condition. These results show that the adaptive and modulation coding (AMC) modulation scheme has the dynamic ability to alternate among several modulation schemes to maintain optimal performance at all times of the transmission, and compared to fixed modulation schemes this flexibility in AMC produces better data rates and spectral efficiency in communication channels.

4.3. Modulation Classification Using Deep Learning

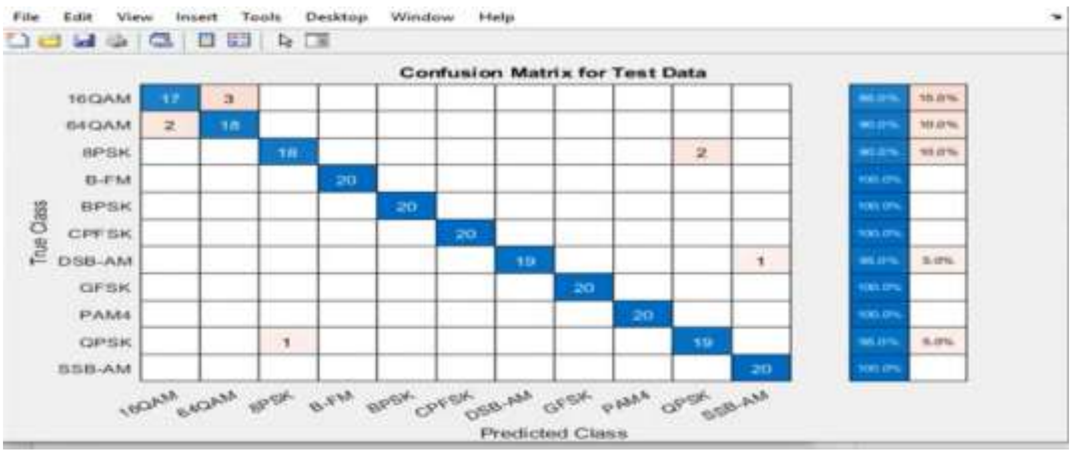

Figure 6: A Confusion Matrix plot showing the test accuracy of the CNN

The convolutional neural network, (CNN), which was the deep learning network used, processes and can be trained with pictures, so a series of frames of random waveforms of the eleven (11) modulation techniques considered were generated and applied to train the CNN, however in this experiment the waveforms were generated, but not used to train a network, an already trained CNN was used as a matter of convenience. The trained CNN was used to perform the modulation classification of a test-transmission operation of all the modulation techniques considered, and a confusion matrix plot was generated, as seen in Figure 4, the result shows there were inaccuracies (confusion) with 16 QAM and 64 QAM, 8PSK and QPSK with 2 64QAM predicted as 16QAM for instance. This implies that the high noise at low SNR can make the higher order modulation schemes overlap due to dense constellation points. Not with-standing a high level of accuracy was achieved with 16QAM 85%, 64QAM 90%, QPSK 100% and BPSK 100%, among themselves. This shows that with augmentation to the training of an AI network channel state information (CSI) inaccuracy can be eliminated, and consequently improving data rate in cellular communication networks.

5. CONCLUSION

The performance of the digital modulation schemes BPSK, QPSK and M-QAM in information transmission has been examined. It has been affirmed that higher order modulation schemes such as the 16 QAM and 64QAM support higher data rates. The use of AMC over traditional fixed modulation schemes for optimal channel utilization, higher throughput has been demonstrated. And the demonstrated performance of AMC which switches state to higher order modulation schemes where lower ones begin to fail has made it outperform other fixed modulation methods and should preferably replace the fixed methods. However the advent of AI has opened a front for modern telecommunication. This study showed that the trained CNN was able to classify the MCS present in the transmitted digital signal using the confussion matrix. This showed that with augmentation to the training of an AI network, channel state information (CSI) inaccuracy can be eliminated, and consequently enhancing automatic modulation and improving data rate in cellular communication networks.

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