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Channel Reconstruction and Quality Prediction in 5G Networks Using Machine Learning Techniques

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ABSTRACT

Device selection, transmission scheduling, control over modulation and the rate of data dissemination through wireless connections are all critical components in managing the network behavior of a 4G and 5G wireless network. If this type of observation becomes widespread, it may overflow the channel, restricting system throughput or causing data loss. As a result, optimizing this signaling system is crucial. This paper aims to optimize the CQI (Channel Quality Index) reporting technique to reduce signaling overhead and avoid overloading the linked channel while also identifying channel quality. Machine learning techniques are used to anticipate the channel's stability. CNN and SVM channel quality estimation algorithms have been implemented.

Keywords: *5G, MIMO, OFDM*

1. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) is a multicarrier modulation (MCM) technology and is considered an intelligent candidate for 4G wireless systems. OFDM provides high ethereal competence that is not affected by the multipath delay and power efficiency that is not affected by low inter-symbol interference (ISI) frequency selective fading. OFDM is used for data transport in optical frequencies such as digital video broadcasting (DVB) and global mobile connectivity (mobile WiMAX). Despite this, the OFDM structure is susceptible to PAPR issues. OFDM systems combine several subcarriers to produce a single output. In this case, the instantaneous control output increases significantly or can be much higher than the average power of classification. Sending these high PAPR signals requires very high-power ranges and power amplifiers. These kinds of amps are very expensive. If peak power is too high, it may be outside the scope of the linear control amplifier. This introduces nonlinear distortion or changes in the overlap of signal spectra, which degrade presentation if no measures have been taken to reduce high PAPR [1-2].

2. PROPOSED WORK

Machine learning consists of algorithms that can learn and predict from data. Such algorithms predict or decide by building models from input rather than following instructions from a rigorous program. This series of algorithms have been successfully applied in various applications, such as computer security, bioinformatics, computer vision, medical diagnostics, and search engines. These platforms have in common: they automatically process database data to generate valuable insights and make informed decisions. Mobile networks are generally complex, and it is expected that the next 5G connectivity systems will be more complicated. They need to deal with more and more scenarios that can't be fully communicated with today's mobile plans, such as multiple deployments of powerful power lines, intelligent transportation systems, low latency connectivity, and networks company. To address this complexity requires establishing intelligent ways to analyze 5G data. These methods need to reduce the workload of network management, i.e., reduce the human resources required to manage these communication networks, generate information, and predict future network and user behavior to make decisions. -more ideas. This will result in higher network efficiency [3-5].

2.1 CHANNEL QUALITY INDICATOR

The Channel Quality Index (CQI) indicates how well a wireless channel communicates. A CQI can be a single number (or a data collection) that indicates a channel's quality metric. Signal-to-noise ratio (SNR), signal-to-interference plus noise ratio (SINR), and signal-to-noise plus distortion ratio (SNDR), among others, can be used to calculate CQI for a channel. These values can be computed on a channel and then used to calculate the channel's CQI. The CQI of a channel can be affected by the communication arrangement's transmission (modulation) mechanism. For instance, a communication System that uses code division multiplexing (CDMA) can employ a more diversified CQI than one that employs orthogonal division multiplexing (OFDM). The CQI employed may vary according to the receiver type in more complicated communication systems, such as engaging multiple-channel input (MIMO) or space coding. Additional considerations that can be considered in CQI include the demonstration's inability to perform as planned, such as Doppler shift, channel evaluation, and interference [6].

2.2 AI AND ML IN MOBILE COMMUNICATION NETWORKS

Artificial intelligence is a branch of science that entails programming machines to emulate human behavior to perform jobs that people excel in (natural language, speech, image recognition, etc.). Artificial intelligence is a field that lies at the nexus of numerous branches of computer science and applied mathematics. According to the artificial intelligence perspective, we as humans intuitively understand what intelligence is and can thus determine whether a machine is intelligent. With his famous "Turing Test," Alan Turing (Alan

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Turing) proposed this practical concept of artificial intelligence in 1950. If a computer can communicate, the Turing test is valid. The machine is considered intelligent if it cannot discern the difference between this and a human, the machine is considered intelligent [7]. The initial attempt at artificial intelligence was to model biological neurons in the brain. For the first time, [8] conceptualized the artificial nerve as a binary variable that could be turned on or off in 1943. Donald Hebb created a neural network learning method in late 1949. Marvin Minsky and Dean Edmonds constructed the first neural network computer, the Stochastic Neural Simulation Augmentation Calculator (SNARC) in 1951. In 1956, a small group of researchers interested in intelligence study convened a two-month seminar at Dartmouth University to commemorate this accomplishment. According to popular perception, John McCarthy introduced and defined the term artificial intelligence during this seminar as follows: "Artificial intelligence refers to machines that are capable of executing activities that need human intelligence." Artificial intelligence has piqued scientists' and industries' curiosity in recent decades. This is due to the fact that AI is used in a wide range of fields, such as natural language processing (news transmission, speech-to-speech translation), healthcare (assisted surgery, computer-assisted diagnosis), smart cars and drones (self-driving cars, obstacle detection), and mobile networks (e.g., performance optimization, traffic forecasting).
The relationship between machine learning, deep learning, and AI In today's world, artificial intelligence is a collection of technologies that work together to enable machines to mimic human intelligence. The first artificial intelligence methods were rule-based expert systems. Because of recent advances in artificial intelligence, many people misunderstand that artificial intelligence is for machine learning. The Machine learning discipline emerged a few years after its birth to develop AI capable of understanding and absorbing information.

Machine learning is a subset of artificial intelligence that enables computers to execute tasks without explicit instructions on how to do them. A paradigm tries to create a computer capable of learning the same way humans do. The learning process entails providing machine learning algorithms with examples of tasks (data) to perform and allowing the computer to discover patterns and make the best decisions based on customized goals. In general, machine learning can be used for various tasks, including classification, clustering, and data prediction. The Artificial Neural Network (ANN), alternatively referred to as the Neural Network (NN), is a widely used machine learning model inspired by the brain's biological operations. Perceptron was Rosenblatt's first neural network method in 1958 [9].

3. PROBLEM STATEMENT

The LTE system gave way to the 3GPP/NR system, which allowed for different subcarrier spacing configurations and NR numerology in the time domain. NR's basic frame structure is granular and slotted. When subdivided, the number of slots included in each subframe can be flexibly adjusted in accordance with the subcarrier spacing. In this case, a frame can be divided into multiple slots, allowing scheduling decisions to be made in less time, which is referred to as the Transmission Time Interval (TTI) [10]. Each Resource Block (RB) in the frequency domain is made up of 12 subcarriers and is subject to its own set of propagation and interference conditions. These conditions are analyzed on the user side and communicated to the base station (BS) as the channel quality indicator (CQI), allowing the BS to use the frequency diversity of the radio channel. Generally, excellent spectral efficiency is achieved by dividing the bandwidth into several tiny sub-bands for each user in OFDM access used in NR and LTE systems. The scheduler's ability to acquire precise real-time input on channel quality indicators (CQI) is critical for achieving high scheduling efficiency [11].

4. OBJECTIVES

- To efficiently do the precoding operations.
- To improve the performance of the proposed system.
- To show better results than the conventional methods

4.1 Convolution Neural Network

The entire connection model is primarily concerned with resolving issues associated with the physical medium in the 5G system. This makes sense because the physical data is typically structured (e.g., CSI, Channel Quality Index (CQI), Radio Relationship Information, and so on). Additionally, many works omitted more complex data, such as historical data. Unsurprisingly, the physical 5G layer has garnered so much attention. This is the application situation for several novel technologies, including millimeter-wave, multiple-input outputs, and beamforming antennas. These are complicated technologies that require continuous fine-tuning. Although the fully linked layer is not meant to process sequential data, some research cited in this system assessment suggests a time series model. In [12] real-world data is available of mobile networks, such as internet usage, text messages, and phone calls. Even though the dataset contains spatial-temporal functions. The author removes them to create a fresh input for the deep learning model. In [13], the author developed a fully integrated approach for coordinating the processing of user inputs. However, a deep learning model comprised of fully connected layers was employed to process the data [14]. Reinforcement learning techniques are used with the fully linked model. A Mininet public open-source simulator provides a network topology (environment) to train the agent in this study. The deep learning model is then utilized to decide the best course of action for the environment.
CNN comprises sophisticated layers: image filter sets embedded in images or cards and additional layers (e.g., pooling). We have repeatedly erased the extensive and sophisticated distribution sheet in the image organization and article card, or the network has eventually released the label displaying the projection category. Taking the training data set into consideration, CNN differs from traditional machine learning approaches that rely on human processes. It improves the secret layer weights or riddle settings to produce features that address organizational issues. Backpropagation or inclined

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parenting procedures alter network parameters to reduce classification errors. These strategies successfully positioned elements in the image or obtained basic functionality. They are, however, usually based on CNNs that utilize ImageNet and contain images from a variety of sources (1000 categories). The distinction between rice disease data and other data collections, on the other hand, is that the organization must modify and expand the function. Without a doubt, the

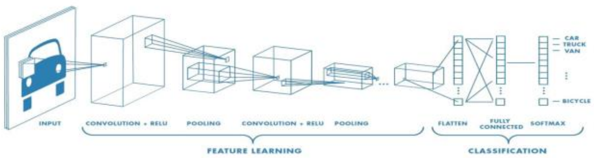

Figure 1: Convolution Neural Network [5]

classification of a cat's or dog's disease is because the former depends on minute differences in comparison to the latter (for example, the appearance of injuries on the leaves). The researchers use imaging devices to extract signs of rice disease from qualifying CNNs and compare this visualization method.

Figure 1 shows the Convolutional Neural Network Layers - CNN is a deep learning system that may assign input photographs to specific aspects/objects in the image or identify them. CNN is an algorithm for deep learning. ConvNet's pre-processing requirements are significantly lower than those of other organizational methods. ConvNets can acquire these filter properties manually or after sufficient training, in the way of the present invention. ConvNet development can be linked to the connectivity of human brain neurons, or the association of the visual cortex can stimulate it. In the controlled field of vision, a single neuron responds solely to the stimulus, referred to as the excitatory field. These fields overlap and include the entire visible area.

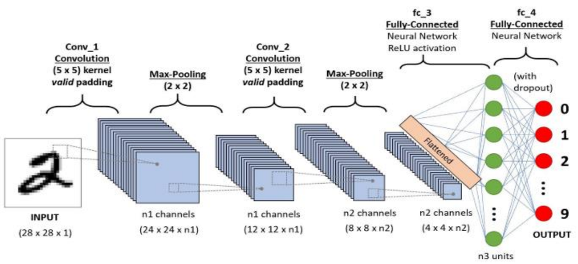

Figure 2: CNN Layer [5]

Max Pooling can also be used as a suppressor. It decreases both noise and dimensionality. The average pooling technique is only used to reduce the size of noise. As a result, "max pool" performance much outperforms "average pool."

Stage-Ensemble Classifier The external score kit used in this work is a novel method based on CNN feature extraction and thanksgiving. The SoftMax layer served as the foundation for the standard CNN stage. Our future system will use a powerful set of classification techniques to achieve categorization. We sent features acquired from the CNN model's three deep layers to the external rating system. The CNN system's hierarchical structure comprises many layers, each conveyed through dynamic visuals. Enter a detailed description of the SoftMax layer, the wrap layer, the pooling layer, and the utterly related layer.

Input layer: The image's pixel value defines the input layer. Original image cannot feed directly to the input layer. We have to convert the input image size before feeding. Because functions are extracted from input data, the problematic layer is known as the collection layer.

Convolution layer: figure 1 shows the CNN layers. The network consists number of layers such as input layer, Convolution Layer, ReLU Layer, Pooling Layer, fully connected layer and SoftMax layers. Multiple convolution layers achieve function removal. The number of removed sections is proportional to the number of neurons in the sample layer. The input data represented in the equation can always be better covered by raising the depth of the complex layer.

$$HKM = f\,(x_m * w_k\, m + b_K m) \;\ldots\ldots\ldots\ldots\ldots\; (1)$$

$X_m R$ input sets are among them, w represents the kernel, and the Start function f is used in the formula. There are several types of initial functions, including Sigmoid, t, and one-way linear unit (ReLU). In this study, ReLU was used as the activation purpose for the entanglement layer, with

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

Pooling Layer: Because it summarizes and maps the current information for each field in a specific local area, the pooling layer is unavailable. The pool with the largest size in The Eq. 2 can be displayed.

$$hm+1\ k\ (i) = \max\,(hkm\ \ (nm+1\ (i-1)+1\ ),\ (\ hkm\ \ (nm+1\ (i-1)+2\ ) \ldots (\ hkm\ \ (nm+1\ (i-1)+N\ ) \ldots (2)$$

N is the length of the braid window among them. N_{m+1} is referred to as the step or the margin between two merged windows.

Fully connected layer: The convolution or pooling layers' learned graph will be flattened to a one-dimensional moral area. It is also known as the dense layer because each neuron is linked to the output layer via teachable parameters.

SoftMax layer: The final output layer, SoftMax, contains many neurons and the same classes as the classification task. Each of the categories is assumed to have a probability cycle. Current neural networks based on SoftMax classification and classification units as functional extracts demonstrated exceptionally accurate image recognition capability [15].

4.2 CQI PREDICTION MODULE

5G networks provide higher bandwidth or more sophisticated management to improve the user experience while requiring more accurate channel estimates than previous mobile networks. This thesis proposed a method for predicting the Channel Quality Index (CQI) in a machine learning approach, including the CNN and SVM algorithms [16]. In typical cellular communication, the transmitted signal encounters unpredictability due to reflection, diffraction, and signal scattering. Furthermore, using the gNB's standard reference signals, the UE measures and estimates the downlink SNR and generates a consolidated Channel State Information (CSI) report. The Channel Quality Indicator is an important component of the CSI report that provides information to the

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gNB (CQI). Based on the CSI report, the gNB allocates appropriate radio resources to the UE in order to maintain a specified level of Quality of Service (quality of service). The CQI parameter of the CSI is used by gNB to determine the best Modulation and Coding Scheme (MCS) to use between the gNB and the UE to correct channel impairments and minimize the number of re-transmissions. Inadequate CQI results in an uneven distribution of radio resources during resource scheduling among UEs, as well as incorrect MCS, resulting in a significant loss of quality of service and UE performance.

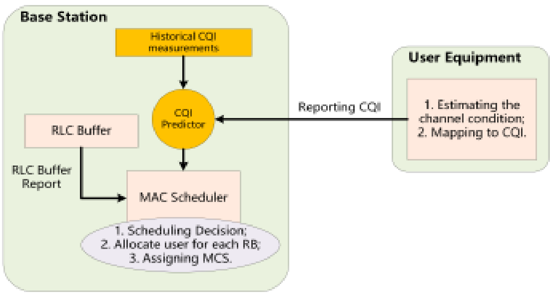

Figure 3: Illustration of CQI Prediction Module

The physical layer resources in the 5G network are not only more plentiful, but also more sophisticated than those in the LTE network. As a result, more adaptable and dependable scheduling algorithms, as well as more precise CQI values, are critical for NR network enhancement.

In the NR system, a downlink scheduler (MAC Scheduler) is located at the medium access (MAC) layer. It receives scheduling information from each user who connects to the base station, such as CQI, buffer status reports (BSRs) from the Radio Link Control (RLC) layer, and Quality of Service (quality of service). The scheduler then assigns a user to each RB based on the information that was previously specified. As RBs are distributed to users, the MCS is computed using the CQI value, which defines the Transport Block Size (TBS). The MCS and TBS are in charge of the data transfer during this time period. Users report the CQI at each scheduling interval. When the base station receives CQI feedback, both the base station's request and the transmission of CQI will cause a delay [17].

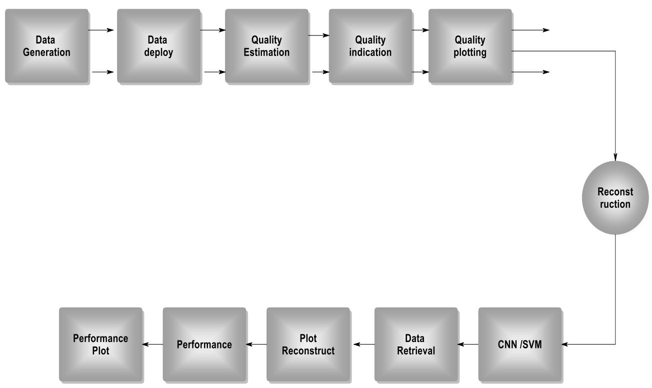

Figure 4: Flow Diagram

4.2 MODULES

- Data Deployment
- Weak Node Detection
- Weak node Reconstruction
- Performance Estimation

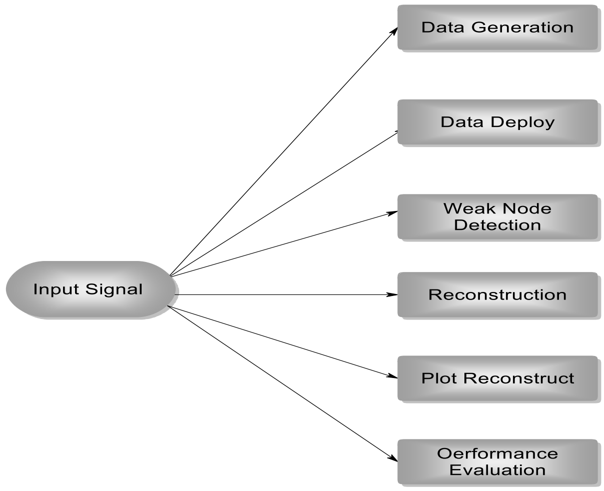

Figure 5: Use Case Diagram

MODULES DESCRIPTION

Symbol Generation

It uses multiple parallel narrowband subcarriers to transmit information instead of a single broadband carrier. OFDM is essentially the same as coded OFDM and DMT (Discrete Multitone Modulation) in the FDM (Frequency Division Multiplexing) scheme used in digital multicarrier modulation schemes. It is utilized in various applications.

In the OFDM scheme, many orthogonal nested narrowband subchannels or subcarriers communicate in parallel, dividing the available transmission bandwidth. Because subcarrier separation is tentatively minimal, very compacted spectral utilization is possible. The appeal of OFDM stems primarily from the system's handling of multipath interventions on the receiver. Selective frequency fading or inter-signal interference are caused by multipath (ISI). A narrow band channel's perception of "flatness" defeats the first channel. Modulating at a low symbolic rate causes the symbol to be much longer than the channel's response to its impulses and causes it to decrease. The use of solid error correction codes with time or frequency interleaving provides more excellent stability against frequency selective fading, which can further reduce the impact of ISI by inserting an additional guard interval between successive OFDM symbols. So, there is no need for an equalizer in the receiver. Data is individually modulated randomly generated per user. Following the modulation technique, the constellation symbol is precoded with DCTM. Precoding reduces the autocorrelation between modulated data, and subcarrier mapping is performed in a localization mode, such as the 4GLTEA cellular network. Before IFFT, each user is assigned a certain amount of power in a power domain. The recipients have deployed MUDSIC to manage the numerous users carefully they have accumulated.

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To obtain likely modulation data, the following applies the inverse of the DCT precoding matrix P-1 (because I = P.P-1).

RRC Filtering Model

An ideal ascending cosine filter's frequency response consists of a single benefit at low frequencies, an ascending cosine function in the middle, and total attenuation at high frequencies. The roll-off coefficient constant Alpha determines the width of the intermediate frequency (0 Alpha = 1). In the filter solution, the passband frequency is defined as the signal attenuation point of 50%. Group delay should be kept constant within a range of at least 15-20 dB of attenuation. When the ascending cosine filter's passband frequency is adjusted to half the data rate, the first criteria of impulse comeback Nyquist with a T = NT impulse response is satisfied. Where N is a number and T is the data's duration. Filter Solutions manufactures rising cosine filters in analog, IIR and FIR configurations. FIR is the most accurate and convenient method to utilize. However, an analog filter may produce an inexact rising cosine response if an FIR filter is unavailable.

The higher order of the filter, the more excellent Raise Docomo sine approximation. Higher-order race doctrine filters also manufacture longer time delays. A lower alpha value reduces bandwidth usage but increases ISI due to errors in element values and design flaws. Filter the input signal using either a regular Raise DoCoMo Sign FIR filter or a Square Root Raise DoCoMo Sign FIR filter to cut up the filter samples by sending a Wraith doco sine filter. Low-pass filters, known as wraith docosine filters, are frequently employed in data transmission systems to shape the pulses (modems, etc.). | H (f) | Frequency response the full-race docosine filter is symmetric around 0 Hz, segmented into three sections, and passband flat (constant). It converges on zero via an elegant cosine curve in the transition zone. Outside the passband, it is a value of zero [18].

4.3 DCTM PRECODING MODEL

Free coding is a preprocessing method that executes transmit diversity and is similar to lighting. With main difference is that the decoder must optimize the precoder. Channel equalization aims to decrease channel error, while free programmers aim to minimize receiver output error. By balancing information streams, free coding exploits transmission diversity. The transmitter transmits encoded data to the receiver for the receiver to get prior knowledge of the channel. The receiver is a straightforward detector, similar to a matched filter, requiring additional channel information. This technology mitigates the negative impact of the communication channel on the environment. Precoding is accomplished by multiplying the modulated data from each OFDM block by a precoding matrix before allocating some IFFT blocks. The precoding matrix has the exact dimensions as the vector of assigned subcarriers. The projected precoding scheme is constructed by multiplying data symbols by a precoding matrix before some subdivisions. The pre-coded sequences of DCTM have lower sidelobes compared to sidelobes of the non-precoded sequences. A low sidelobe value indicates a low autocorrelation, and a high sidelobe value indicates a high autocorrelation. A low autocorrelation of the IFFT input means that it is less likely to add in phase with the IFFT. Therefore, PAPR is reduced [19].

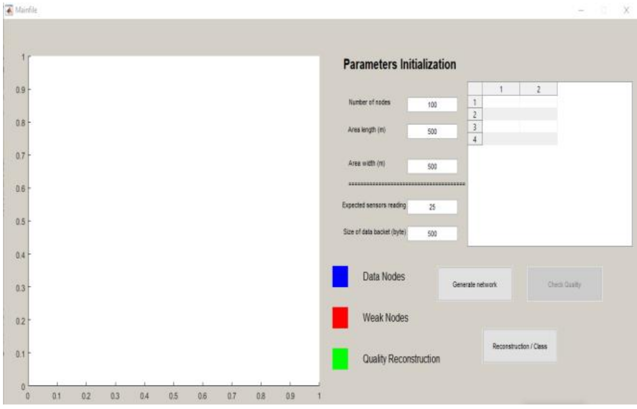

Figure 6: Parameters Initialization

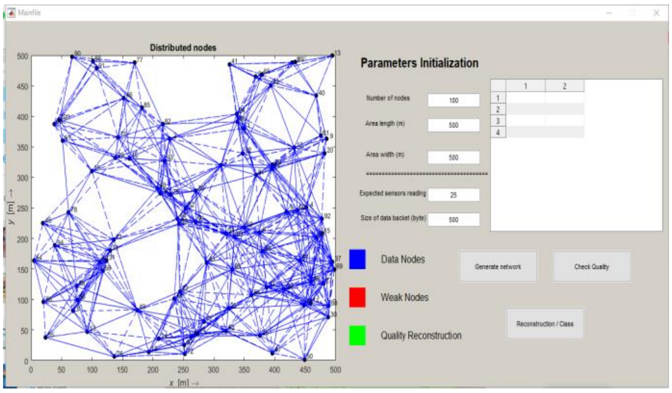

Fig. 7: Network Creation and Node Deployment of Nodes

4.4 QPSK MODULATION

QPSK is a phase modulation technology in which two bits of data (integrated into a single symbol) are changed simultaneously to select one of four possible carrier phase shift states.

$$S(t) = A\cos[2\pi f_c t + \theta_n] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

QPSK uses four points in a constellation diagram that are spaced circumferentially. You can encode 2 bits per QPSK symbol in step 4. This is shown in the grey code graphic to reduce the bit error rate (BER). The BER of 2x BPSK could be deceptive. According to a mathematical study, QPSK may be used to double data compared to BPSK while maintaining the same signal bandwidth or halting the bandwidth required while retaining the BPSK data rate.

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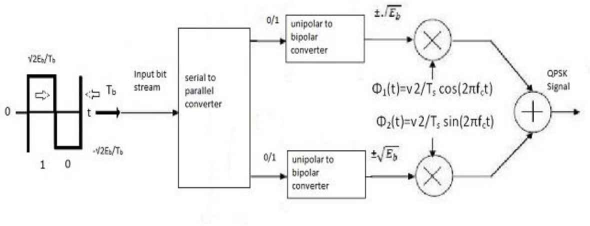

Figure 8: QPSK Modulator

In above instance, the BER of QPSK is identical to the BER of BPSK, and alternative decisions can be made, a common misunderstanding when analyzing or discussing QPSK. A transferred career can give you some phase shifts. It is a QPSK (Quadrature Phase Shift Keying) modulation technology, exciting because it essentially transmits 2 bits per symbol. This means that the QPSK symbol does not represent 0 or 1, but rather 00, 01, 10, or 11. Because carrier variation is not confined to two states, these symbols are presented in two-bit format. For instance, in ASK, the carrier amplitude is specified as Amplitude Option A (showing 1) or Amplitude Option B (saying 2). (Indicating 0). It is phase-dependent, not carrier frequency-dependent, in QPSK, and there are four conceivable phase shifts.

4.5 PERFORMANCE EVALUATION MODEL

Bit Error Rate (BER) - The Bit Error Rate (BER) is a metric that measures the number of bit errors per unit of time. The bit error rate (BER) is calculated by dividing the number of bit errors by the total number of bits transferred during the time period under consideration. BER is frequently expressed as a percentage less units in performance measurements. The expected bit error rate is used to determine the likelihood of a bit error. The bit error rate can be thought of as a proxy for the likelihood of encountering a bit error. For time intervals greater than one second and multiple bit errors, this estimate is accurate. For QPSK and AWGN modulation, the BER as a function of Eb/N0 is given.

$$BER = \frac{1}{2} erfc((\sqrt{E_b/N_0})\text{.............................} (4)$$

The mean square error (MSE) and peak signal-to-noise ratio (PSNR) evaluate picture compression quality. The MSE statistic indicates the cumulative squared error between the compressed and original image, whereas the PSNR statistic indicates the peak error. The MSE value is inversely proportional to the mistake.

Peak signal-to-noise ratio (PSNR) -The phrase peak signal-to-noise ratio (PSNR) refers to the ratio of a signal's maximum possible value (power) to the strength of distorting noise that degrades the quality of its representation.

$$PSNR = 20XLog(MAX_i) - 10XLog(MSE)\text{.......} (5)$$

MAX_i denotes the image's maximum potential pixel value. This is 255 when the pixels are represented using 8 bits per sample. In general, MAXI equals 2B1 when samples are encoded using linear PCM with B bits per sample.

Mean squared error (MSE) - An estimator's mean squared error (MSE) or mean squared deviation (MSD) is the average of the squares of the errors—that is, the average squared difference between the estimated and actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \dot{Y}_i)^2$$

MSE} = mean squared error
{n} = number of data points
Y{i} = observed values
{Y}{i} = predicted values

Table 1: Comparison Result with Exiting Work

	Algorithm	Accuracy	MSE	PSNR	TRP
Proposed Work	CNN	99.94%	1.058	47.88	0.12
Existing Work	SVM	96.43%	1.236	43.24	0.11
		92.86%	1.436	39.24	0.12

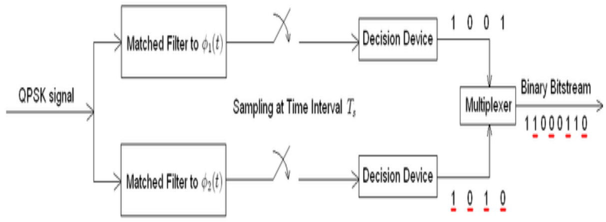

Figure 9: QPSK Demodulator

5. CONCLUSION

Therefore, a convolution neural network technique for channel quality prediction is proposed. This technique must maintain the system's spectral competence or BER performance. In this proposed arrangement, input signal data is first generated erratically, and then the generated data symbols are modulated. The proposed arrangement employs QPSK modulation for this purpose. Following modulation, signal data is converted from serial to parallel format and processed. The transformed similar information is subjected to the Fourier transform process, or the signal is filtered using the corresponding filter. After the proposed method has precoded the signal, it is passed through the channel and the inversion operation is performed. As a result, a precoding-based PAPR reduction technique has been proposed. The receiver can decode the received symbol without sending "side information," thereby maintaining good spectral organization. In addition to PAPR, the AWGN channel saves the BER and MSE.

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