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Assessment of Channels Modelling, Demodulation, Coding in 5g Wireless Communication System Using Two-State Markov Chain

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Abstract
In fifth-generation (5G) wireless communications, efficient data transmission is hindered by burst errors and packet losses resulting from multipath fading. To enhance reliability and mitigate degradation in 5G networks, it is crucial to analyze error patterns and sequences. This paper investigates and develops a two-state Markov-based error model tailored for 5G networks to capture the statistical characteristics of the error process. The model is derived from simulations of 5G wireless networks employing various modulation schemes—Quadrature Phase Shift Keying (QPSK), 16 Quadrature Amplitude Modulation (16-QAM), and 64 Quadrature Amplitude Modulation (64-QAM)—combined with Low-Density Parity-Check (LDPC) and Turbo coding methods. By comparing the burst or gap error statistics from our 5G simulation with those generated by the two-state Markov error model, we demonstrate that the Markov model accurately reflects the error behaviors observed in coded Orthogonal Frequency Division Multiplexing (OFDM) 5G simulations. The two-state Markov model provides valuable insights into the error processes of 5G communications and allows for the evaluation of error control strategies with reduced computational complexity and shorter simulation durations. This approach facilitates a deeper understanding of error dynamics in 5G systems and supports the development of more effective error management techniques.

Keywords: 5G, Burst Error Statistics, Two-State Markov Model, Wireless Error Model

Introduction

The fifth generation (5G) wireless technology is set to revolutionize network performance with significant enhancements in speed, coverage, and responsiveness. Users expect 5G networks to be user-friendly and multifunctional. To meet these demands, the fifth-generation technology must utilize efficient waveforms to improve bandwidth, spectral efficiency, energy consumption, signaling, and reliability. Orthogonal

Frequency Division Multiplexing (OFDM) is a prominent multiplexing technique widely used in high-performance wireless transmissions. While OFDM effectively mitigates multipath fading and intersymbol interference (ISI) by incorporating a cyclic prefix (CP), it still suffers from intrablock OFDM symbol interference, which degrades error performance.

To address this issue, integrating channel coding methods with OFDM systems has emerged as a crucial solution to enhance bit error rate (BER) performance and recover data symbol losses. However, OFDM systems are also challenged by high peak-to-average power ratios (PAPR), which lead to nonlinear distortions and performance degradation. Channel coding methods, such as Turbo codes, LDPC codes, and convolutional codes, are critical for mitigating these issues and improving overall system performance.

Evaluating channel coding methods' effectiveness in next-generation wireless networks requires understanding physical and binary channel models. Physical channels, such as Rayleigh and Rician fading channels, are assessed based on metrics like received signal strength and signal-to-noise ratio (SNR). Binary channels are characterized by error statistics, focusing on burst errors or error clusters, with performance evaluated through metrics like BER and packet error rate (PER). Understanding burst error processes and their statistical dependencies is essential for optimizing wireless data transmissions.

This study employs both statistical and deterministic approaches to model 5G wireless channels' physical and error characteristics. The research emphasizes the importance of error patterns, including single-bit and burst errors, to enhance wireless data transmission optimization. To model burst error sequences, the study differentiates between descriptive and generative models. Descriptive models use real or simulated data to capture error statistics, while generative models replicate these patterns based on descriptive insights.

A simulation model was developed and evaluated to support the design of a coded OFDM 5G simulation. The model's statistical behavior, particularly error sequences, was analyzed descriptively to improve communication models' accuracy and reliability. Subsequently, a generative error model using a discrete-time, two-state Markov chain was proposed. This model aims to provide precise burst error statistics and optimize BER performance in 5G communications. Comparing error statistics from both descriptive and generative models revealed similar characteristics, confirming the effectiveness of the two-state Markov model in capturing the error processes of coded OFDM 5G simulations.

The primary motivation of this research is to enhance the accuracy and performance of data transmissions in 5G networks by investigating and modeling errors in the coded OFDM simulation. The study's contributions include the development of a coded OFDM 5G simulation based on LDPC and Turbo coding, descriptive analysis of the error process, and the proposal of a generative error model using two-state Markov chains. The results demonstrate that the proposed error models effectively represent errors in coded OFDM 5G networks. These models offer a cost-effective and time-efficient approach to evaluating and implementing error control mechanisms by generating accurate error sequences without the need for complete simulations.

The paper is structured as follows: Section 2 reviews relevant literature. Section 3 provides a brief overview of the proposed coded OFDM 5G simulation model. Section 4 discusses the

analysis and results of LDPC and Turbo coding methods in 5G OFDM simulations. Section 5 explains the two-state Markov-based error model and the proposed error model, including parameter estimation. Section 6 presents the simulation and analytical results. Finally, Section 7 concludes by demonstrating that the simulation model aligns with the proposed analytical model.

Review of Literature

In the realm of next-generation wireless communications, the fifth-generation (5G) technology has emerged as a foundational standard, offering impressive high-performance attributes such as accelerated data transmission rates, reduced latency, significantly increased system capacity, energy efficiency, and enhanced Quality of Service (QoS) [24], [25], [30]. Despite advancements in these areas, challenges persist, particularly in managing interference, modeling channels, and addressing signal processing complexities during data transmissions [24]. Research indicates that improvements in transmission technology are largely driven by factors such as modulation constellations, coding schemes, and effective channel and resource allocation. These research challenges are influenced by various elements including transmission power, duration, channel conditions, and the employed coding and modulation methods [30].

To tackle these challenges, previous studies have analyzed the integration of channel coding schemes with Orthogonal Frequency Division Multiplexing (OFDM) systems. These analyses underscore the critical role of channel coding in enhancing data transmission performance in 5G networks [8], [20]–[22]. Channel modeling and error modeling have become key research topics, with numerous studies focusing on the exploration of error statistics and the development of error models [15]–[18].

For instance, research has examined the impact of bit error processes on packet transmission by implementing a 2-state Markov model over error channels [1]. This study utilized a closed-form solution for parameterization and investigated the performance of error correction codes under both random and burst errors. Other studies, such as those by Ling-Jyh and Hao-Hsiang [2], applied two different error models to Bluetooth networks using Frequency Hopping Spread Spectrum (FHSS) kernels, employing Markov Chain Monte Carlo (MCMC) methods to validate the simulation and analytical results.

In another study [3], the Bit Error Rate (BER) performance of Digital Audio Broadcasting (DAB) systems using convolutional and turbo-coded OFDM in Additive White Gaussian Noise (AWGN) channels was analyzed. Additionally, research focused on burst error behavior and error profiles in fading channels using a tri-state memory-less Markov model, demonstrating that larger data packets lead to more extended burst errors and higher BER [4]. This research involved simulations with various packet sizes and highlighted the relationship between packet size and error behavior.

Generative error models, including the Simplified Fritchman Model (SFM), the Baum-Welch based Hidden Markov Model (BWHMM), and the Deterministic Process Based Generative Model (DPBGM), have been proposed to address these issues [16]–[18]. These models, which consider detection thresholds, parameterizations, and parallel mappers, have shown

effectiveness in matching reference error statistics from descriptive models with those generated by the generative models, particularly in terms of burst error statistics and BER performance.

In summary, error modeling using real simulation models is a critical research area for enhancing wireless data transmission in future network technologies. This paper proposes and evaluates a two-state Markov error model based on our coded OFDM 5G simulation. The goal is to assist in the development of error control schemes that can reduce transmission errors and improve performance in 5G networks.

Description of the Coded OFDM 5G Simulation

In previous work [8], we presented a simulation framework for a coded Orthogonal Frequency Division Multiplexing (OFDM) system that aligns with 5G specifications. This framework, depicted in Fig. 1, was designed according to the guidelines provided by the Verizon 5G Technology Forum, specifically the Verizon 5th Generation Radio Access Test Plan release 1 [14]. Within this framework, we utilized and analyzed both Low-Density Parity-Check (LDPC) and Turbo coding methods to assess their performance.

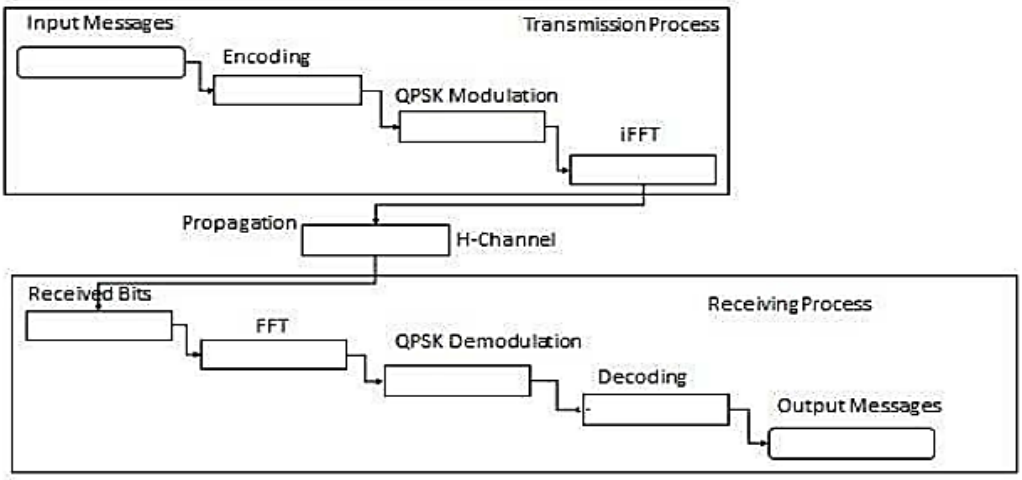


FIGURE 1. Coded OFDM system flow diagram

In the coded OFDM 5G system, we simulated OFDM propagation in an AWGN channel with multipath fading, using a 28 GHz frequency band and a bandwidth of 100 MHz. The system employed 1200 subcarriers with a 75 kHz subcarrier spacing, in accordance with Verizon 5G specifications, and utilized QPSK, 16QAM, and 64QAM modulation techniques. The simulation used an FFT size of 2048, as specified by Verizon.

Input binary data signals are encoded to produce coded information, which includes both the original and additional bits. These encoded bits are modulated using the selected modulation schemes and then mapped onto the N subcarrier channels. The Inverse Fast Fourier Transform (iFFT) converts the frequency domain data to the time domain for transmission over the

multipath AWGN channel. Received signals are then converted back to the frequency domain using FFT and demodulated to recover the original data bits.

The code rate is represented as R=k/nR = k/nR=k/n, where kkk is the number of information bits, nnn is the number of variable nodes, and mmm is the number of check nodes. The parity check matrix HHH is constructed based on the code word length, and the encoded bit length LLL is calculated as K×1/RK \times 1/RK×1/R. The modulation process maps these encoded bits using the number of subcarriers NNN.

$L(\text{mod } i) = E/F_i$,(1)

In the 5G OFDM simulation, the modulation methods QPSK, 16QAM, and 64QAM are applied. Due to a mismatch between the actual number of subcarriers NNN and modulated bits, we use a mapping approach to align the modulated bits with NNN subcarriers for accurate propagation.

$L_c(\text{mod } i) = E/F_i + N/2$ (2)

In uncoded OFDM 5G communications, the number of information bits BBB, where B={B0,B1,B2,…,Bn−1}B = \{B_0, B_1, B_2, \ldots, B_{n-1}\}B={B0,B1,B2,…,Bn−1}, is modulated based on the modulation factor FFF. The length of the modulated bits is calculated using Equation 3, which determines how many bits are mapped to each subcarrier for transmission.

$L_u(\text{mod } i) = B/F_i$ (3)

Here, $L_c > L_u$.

In coded OFDM 5G simulations, modulated bits are converted to the time domain using iFFT, with FFT sizes of 1024 for speed and 2048 as per 5G standards. The LDPC encoder produces a code word and parity check matrix HHH, with the encoded bit length being twice the input signal length for a code rate of 1/2. For instance, with an input of 1200 bits and an FFT size of 2048, the encoded bit length is 2400. This setup highlights the interplay between coding theory, modulation techniques, and FFT in optimizing 5G communications.

Analysis of LDPC and Turbo Coding Methods on OFDM 5G Simulation

In OFDM modulation, input data bits are mapped to subcarrier amplitudes and phases using techniques like BPSK, QPSK, or QAM. This study, aligned with Verizon 5GTF Release 1, examines QPSK, 16 QAM, and 64 QAM as physical channels in 5G OFDM simulations. Table 1 outlines the simulation parameters for the coding process. The performance of LDPC-coded 5G OFDM is compared with uncoded 5G OFDM across the three modulation techniques, as shown in Fig. 2. The results indicate that QPSK offers the best bit error rate (BER) performance among the tested modulations. Furthermore, LDPC-coded OFDM with an FFT size of 2048 consistently outperforms uncoded OFDM in terms of BER across all modulation methods. Additionally, Turbo-coded OFDM simulations were conducted with the same modulation schemes and compared with uncoded OFDM, as illustrated in Fig. 3. These comparisons highlight the advantages of coding techniques in enhancing the performance of 5G OFDM systems.

TABLE 1. Simulation parameters.

Parameter		Values
Coding Schemes		LDPC & Turbo
Code Rate		1/2
Code length/FFT size		1200/2048
Decoding Methods	LDPC	Sum product decoder
	Turbo	BCJR

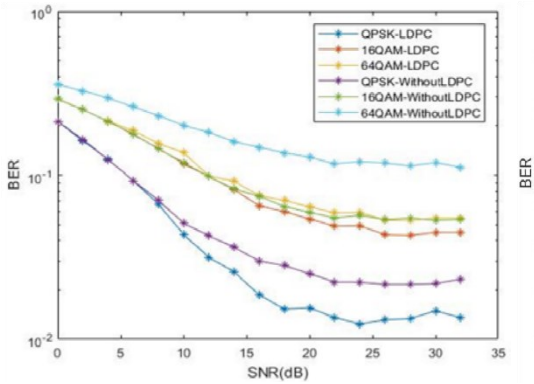


FIGURE 2. BER comparison of the LDPC coded OFDM and uncoded OFDM (fft 1024).

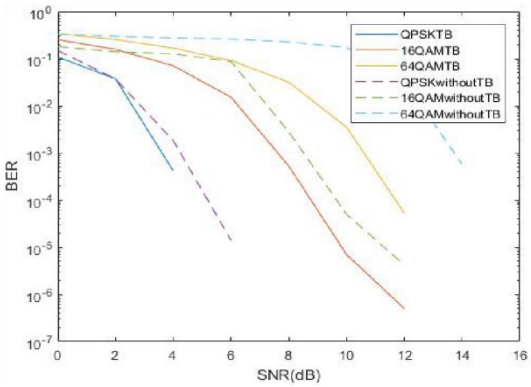


FIGURE 3. BER comparison for the TURBO coded OFDM and uncoded OFDM (fft 1024).

Comparing Turbo-coded OFDM with uncoded OFDM in 5G shows that Turbo coding improves performance across all modulation methods. QPSK consistently achieves the lowest bit error rate (BER) among the modulation techniques for both FFT sizes. Turbo-coded OFDM simulations demonstrate better BER results than uncoded OFDM for both FFT sizes, confirming the effectiveness of Turbo coding in enhancing 5G OFDM performance.

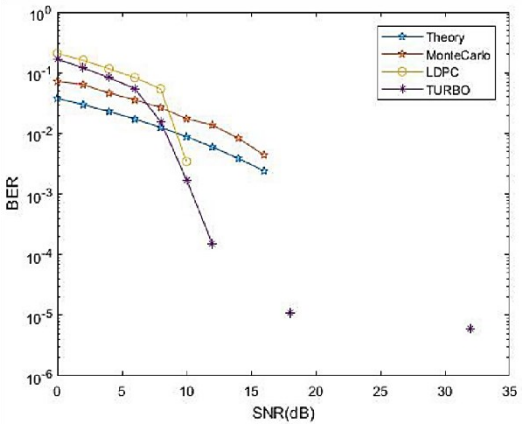


FIGURE 4. BER comparison for the LDPC-coded OFDM Vs turbo coded OFDM (fft 2048).

The simulation results demonstrate that both LDPC and Turbo coding methods achieve lower bit error rates (BER) compared to uncoded OFDM with an FFT size of 2048. Turbo-coded OFDM outperforms LDPC-coded OFDM in terms of BER, as confirmed by Monte Carlo simulations and theoretical results shown in Fig. 4. Previous research supports this finding,

indicating that Turbo coding generally yields better performance than LDPC coding in OFDM systems. Therefore, Turbo codes are recommended for channel coding in 5G networks based on the Verizon 5G Technology Forum's specifications. Turbo coding not only enhances performance but also offers cost benefits due to its backward compatibility with 3G and 4G technologies.

Theoretical Background and Proposed Model

Error Modeling

To accurately model error behaviors in coded simulations, a precise statistical or deterministic error model is essential. This study proposes a discrete Markov model-based error analysis, as illustrated in Fig. 5. In this model, XiX_iXi represents the digital input sequence, while YiY_iYi is the corresponding output sequence, which includes errors. YiY_iYi is treated as a binary discrete-time stochastic process, and NiN_iNi represents the noise sequence caused by multipath channel effects on data packets.

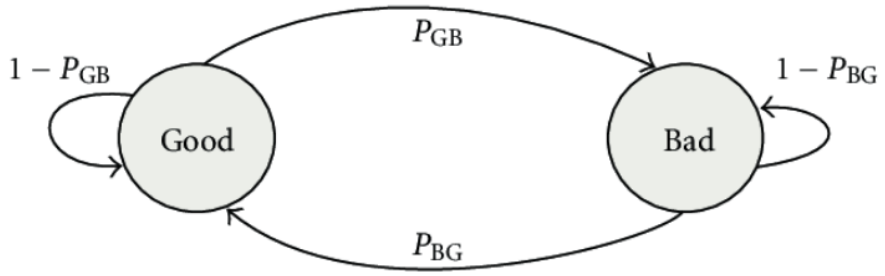


FIGURE 5. Two-State markov-based wireless error model.

Then, $Y = X + N$ (4)

The error process in data transmission is modeled as a binary discrete-time stochastic process, with the binary input represented by the set X.∧ th is the channel $X = [x_1, x_2, \cdots, x_k, \cdots]$, where $X_k = k$ input.

The binary output is the set of Y, $Y = [y_1, y_2, \cdots, y_k, \cdots]$, ∧ th is the channel output, where $y_k = k$; The effective noise on the data packets is N = [$n_1, n_2, \cdots,$ ∧ th is the channel noise. $n_k, \cdots]$, where $n_k = k$

The probability of an error occurring in the data transmis- ∧ sion is PE, PE = [$PE_1, PE_2, \cdots, PE_k, \cdots$], where P_k = is the probability of an error in the k^{th} symbol transmission. For a binary data transmission channel, the input-output relationship can be expressed as $E = X \oplus Y$ (5)

In this model, E={e_1,e_2,e_3,…,ek,…}E = \{$e_1, e_2, e_3, \ldots e_k, \ldots$}, e_k=1 represents a binary sequence where each element is either 0 or 1. A bit is correctly received if e_k=0 and incorrectly received if e_k=1e_k The error sequence is generated randomly based on a threshold.

($1U_k \leq P_k$ e_k =0 $U_k \geq P_k$

In this model, U_k denotes the number generated from the k^{-th} call to the random number generator. To model error sequences, parameters are estimated and expressions derived based

on burst error statistics and their distributions. Burst error statistics are calculated using second-order statistics from segments of the error sequences. According to the literature, error sequences are categorized into two classes: error bursts and error gaps. Error bursts consist of sequences of ones and zeros, flanked by ones at the edges. Error gaps are sequences of consecutive zeros situated between ones, with the length representing the number of zeros. In an error sequence $E=\{e_1,e_2,e_3,\ldots,e_k,\ldots\}$, $e_k=1$ indicates a transmission error at the kkk-th bit, while $e_k=0$ denotes correct transmission. These two types of sequences are expressed as follows: $(0_m|1)$ signifies error-free transmission sequences of length mmm followed by an error, and $(1_m|0)$ signifies consecutive errors of length mmm followed by an error-free sequence. The occurrence probabilities for these events are given by the sum of weighted exponentials.

$$\Pr 0m\,|1) = \sum_{i=1}^{k} fi\lambda mi - 1 \qquad (6)$$

$$\Pr 1m\,|0) = \sum_{i=k+1}^{N} fi\lambda mi - 1 \qquad (7)$$

where λ_i, where i = 1, 2, ⋯, k, and λ_i, where i = k + 1,k + 2,⋯, N, are the eigenvalues of the state transition probabilities A_{gg} and A_{bb}, respectively, and the corresponding values of f_i are functions of the $a_{ij,}$ elements of the state transmission matrix.

Two State Markov Error Model

For modeling the error process in coded OFDM data transmission, a discrete-time two-state Markov model (MM) is used. This model defines two states: good and bad. In the good state, data transmission is error-free, while in the bad state, errors occur with a bit error probability hhh. The model assumes transitions between these states to represent the varying error conditions in the wireless communication channel. Given that data transmission begins at the initial state StS_tSt, the state will transition to the next state St+1S_{t+1}St+1 at time t+1t + 1t+1. The discrete time T can be expressed as the set of times ttt, and the set of states as:

$S = \{G,B\}.$

$T = [t,t+1,t+2\cdots,t+k]$

$S = [S_t,S_t+1,S_t+_2\cdots,S_t+k]$

In the beginning, the channel could be in a good or bad state. It will either shift to a new state or stay in the same state at the introduction of a new bit. A set of transition probabilities, Pij (t), will determine when the state transitions. The four transition probabilities were expressed as follows:

$P_{gg}(t) = Pr\{S_t+_1 = g|St = g\}$

$P_{gb}(t) = Pr\{S_t+_1 = b|St = g\}$ $P_{bb}(t) = Pr\{S_t+_1 = b|St = b\}$

$P_{bg}(t) = Pr\{S_t+_1 = g|St = b\}$

This can be represented by the state transition matrix.

$(t) = |$Pgg Pgb A Pbg Pbb

We define 5_t as the state probability distribution at time t. specifically,

$5_t = [\pi_t, g\pi_t, b]$, where π is the steady-state vector in a Markov chain that represents the overall percentage of a state. By raising P to a high power, the following vector can be calculated: $P^n \rightarrow 1\pi$

In this case, πi must add up to one. P is the matrix of probability transitions. 5 is the probability vector for the steady state.

One is represented by the column vector 1T = (1, 1,). The error generation matrix is therefore defined as follows: Prc Er = Pr, where "e" indicates an error and "c" indicates a correct decision. The unconditional probability of a correct decision (Pc) and an error (Pe) is provided by: |PcPe|= 5tErT^(8), where Er T is the transpose of the error generation matrix Er and 5t is the steady-state state distribution matrix. This can be understood as the result of simple matrix multiplication.

Estimation of Markov Model Parameters

The BaumWelch forward-backward algorithm is a widely utilized and straightforward technique for Markov Model parameter estimation [9], [10]. By leveraging the training data, it facilitates the reduction of computational difficulty in assessing of all model states.The forward path chance and the reverse path probability are two distinct probabilities that were computed to establish the Baum-Wel algorithm. These probabilities can be used to estimate the parameters of the suggested Markov model.

The N × N state transition matrix A and the M × N error probability generation matrix E are used to define the Markov model for a discrete channel. The coded OFDM 5G simulation E = {e1, e2, e3, • • •, et, • • •, eT}, based on the BaumWelch algorithm [11], yields an iterative process for estimating these parameters 0 = {A, Er} from a given error sequence. The goal of this iterative process is to maximize Pr(Er|0) by convergence to the maximum likelihood estimator of 0 = {A, Er}. The following formula can be used to calculate the BMW parameters, which are the estimates of the elements of the error generation matrix and the state transmission matrix: anticipated quantity of changes from i to j Pij = (9) the anticipated quantity of changes from i anticipated frequency of occurrences in state j The expected number of visits to state j is Er(ek). The scaling constant vector Ct is used to scale the forward as well as backward parameters of the Baum-Welch algorithm in order to prevent numerical underflow. For the forward variable αt and the backward variable βt, we may define the scaling constant vectors as follows: N i−1. For iterative approaches, defining the stopping criteria is a crucial difficulty. Given that the Baum-Welch algorithm is an iterative process, it is imperative that the stopping criteria's optimal level be satisfied within the specified accuracy. In order to obtain a precise approximation of the intended parameters for the Baum-Welch method, A and Er, the algorithm can be executed repeatedly until the parameters' elements remain constant across iterations. Because of this, the maximum probability solution can aid in determining the convergence for carrying out the iteration until Pr(Er|0) reaches its ideal value. With the scaling constant vector Ct, the ideal value of Pr(Er|0) can be expressed as follows: YouTube t=1 and Pr(eR/0) = CT^(13).

In this experiment, the log likelihood function is illustrated in Fig. 7.

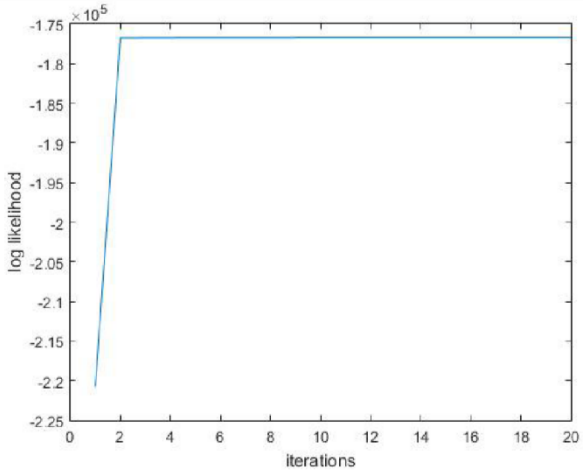


FIGURE 7. Log Likelihood function for parameters A and Er.

The convergence of the log likelihood function's absolute value for several iterations with Eb/No ranging from 0 to 5 dBs is displayed in Fig. 7. After the first few iterations, the Baum-Welch algorithm discovers the local maxima and does not significantly alter. It is evident that the log likelihood function takes approximately two iterations to reach the optimal point for convergence. It should be noted that this result agrees with the previous calculations of Ak and Bk for a total of 20 iterations. Also take note of the extremely low likelihood values, as was previously mentioned.

Simulation Results and Discussion

Two reference error sequences are generated and utilized in this simulation by the coded OFDM 5G simulation, which is based on the LDPC and Turbo codings. They are designated as "experiment" and shown as a blue line. The orange color and the word "model" indicate the error sequence produced by the simulation of the suggested Two-state Markov error model. The probability of error gaps, Pr{0m|1}, and error bursts, Pr{1m|0}, are shown by the x axis, while the length of m observation intervals is represented by the y axis. 170400 bits make up the reference error sequence, which is used in the model simulation training process. The modulation methods all have a burst size of 3. The size of the error-free (gap) varies according on the number of errors.

Simulation Results of the Estimated Markov Model Compared With the LDPC Coded OFDM

The comparison between the error gap Pr{0m|1} of the error sequences produced by the Markov model using the Baum-Welch algorithm and the error gap Pr{0m|1} for the error sequences of the LDPC-coded OFDM 5G simulation is presented in Fig. 8. These simulation results demonstrate that, for the 16 QAM modulations, the error gap probabilities of the LDPC-coded OFDM 5G simulations and the predicted Markov model are symmetrically equal for every interval. However, there is a little variation in the The error burst Pr{1m|0} obtained from the LDPC-coded OFDM 5G simulation error sequences and the error burst Pr{1m|0} derived from the data produced by the model calculated by the Baum-Welch algorithm both show values that are almost in the region of m = 10. For 64QAM modulation and between m = 10 and m = 20 for QPSK.

Nearly identical to those in Figure 9 are the outcomes of the error burst Pr{1m|0} for the error sequences of the LDPC-coded OFDM 5G simulation and the error burst Pr{1m|0} utilizing the data produced by the model determined by the Baum-Welch method. While there is a slight variation between m = 2 and m = 4 for 64QAM modulation, it is evident that the burst error probability of the calculated Markov model and the LDPC-coded OFDM 5G simulation are symmetrically equal for every interval for QPSK and 16QAM modulations. By contrasting it with the Turbo-coded OFDM 5G simulation using the parameters of the error gap probability Pr(0m|1), the error burst probability Pr(1m|0), and the burst error probability PE, the predicted two-state Markov model's performance is also assessed. Every experiment was run through twenty iterations before being assessed. The curves in Fig. 10 for the error gap Pr{0m|1} of the Turbo-coded OFDM 5G simulation error sequences and the error gap Pr{0m|1} derived from the data produced by the model utilizing the Baum-Welch

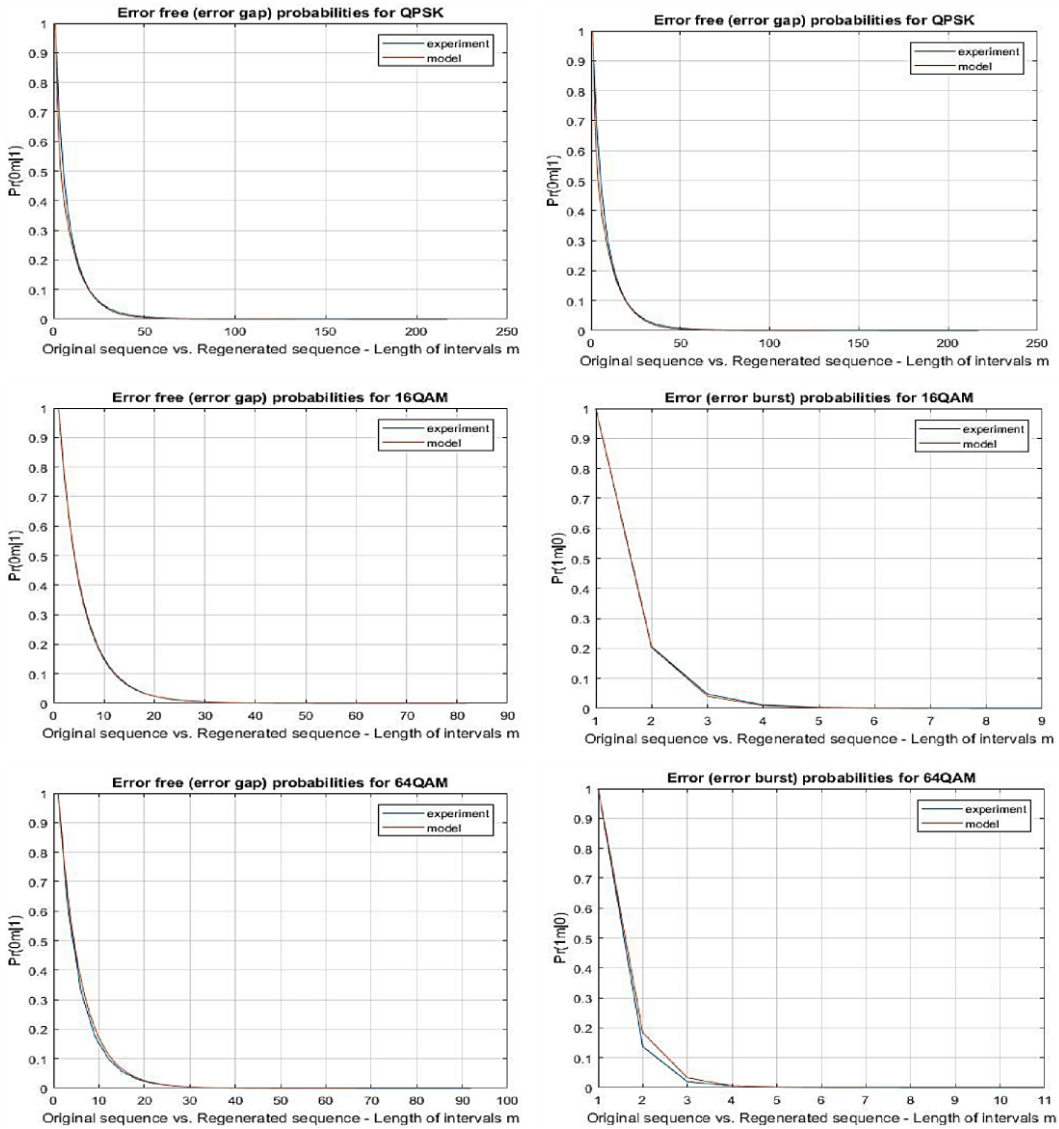


Figure 8: Error Gap histogram for the error sequence of the LDPC-Coded OFDM 5G Simulation and the errorsequence resulting from the 2 state Markov Model

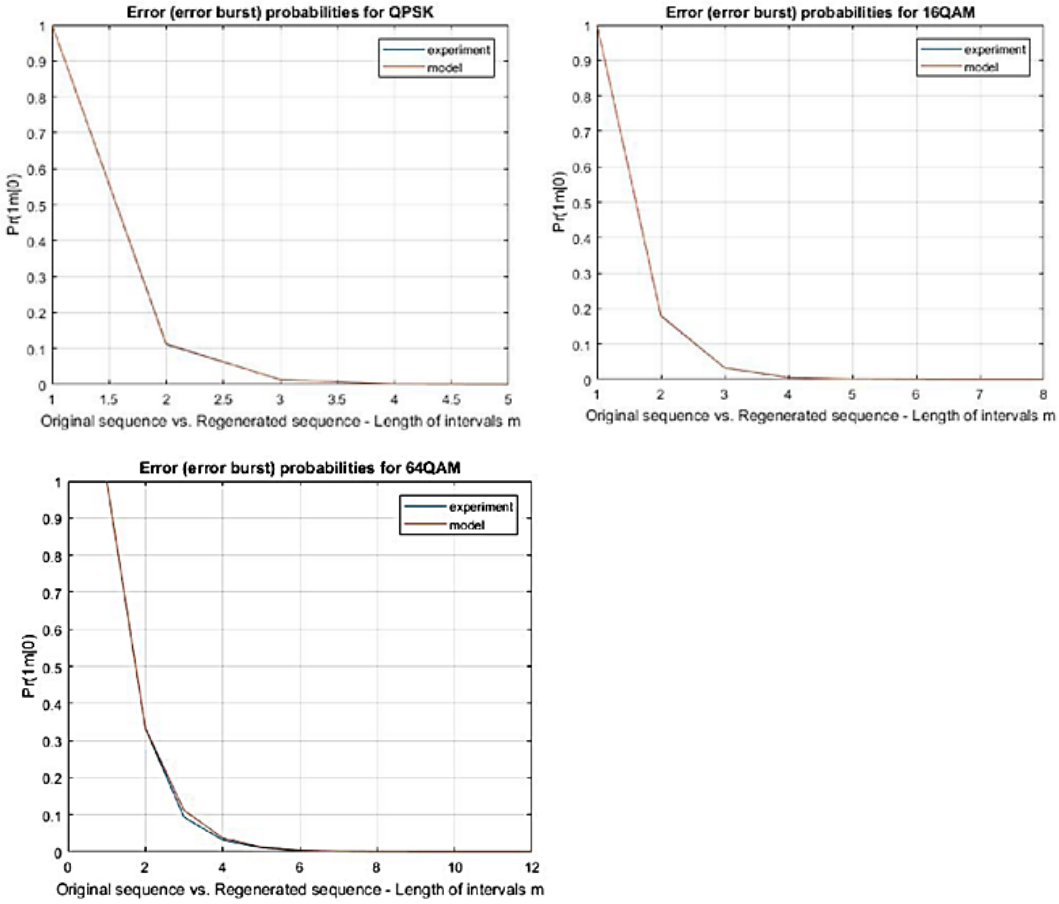


Figure 9: Burst Error histograms for the error sequences of the LDPC-Coded OFDM 5G Simulation and the error sequences resulting from the 2 state Markov model

Summary of Findings

The study evaluated the performance of LDPC and Turbo coding methods in a 5G OFDM system simulated over an AWGN channel with multipath fading, using a 28 GHz frequency band and a bandwidth of 100 MHz. Key findings include:

The simulation used 1200 subcarriers with 75 kHz spacing, QPSK, 16QAM, and 64QAM modulation techniques, and FFT sizes of 1024 and 2048. LDPC and Turbo coding were compared with uncoded OFDM. LDPC coding significantly improved bit error rate (BER) performance across all modulation techniques. Turbo coding demonstrated superior BER performance compared to both LDPC coding and uncoded OFDM.

A discrete-time two-state Markov model was employed to model error processes, representing two states: good (error-free) and bad (error-prone). The model's transition probabilities were estimated using the Baum-Welch algorithm. Error gap probabilities Pr{0m|1}\text{Pr}\{0^m|1\}Pr{0m|1} and error burst probabilities Pr{1m|0}\text{Pr}\{1^m|0\}Pr{1m|0} from the Markov model were found to closely match those from LDPC-coded OFDM simulations, particularly for QPSK and 16QAM modulations.

Figures and tables presented show that Turbo-coded OFDM consistently outperforms LDPC-coded OFDM and uncoded OFDM in terms of BER. The results confirm that Turbo coding offers better performance than LDPC coding in 5G OFDM systems. The Markov model's predictions for error gaps and bursts were nearly identical to those observed in the simulations, validating its effectiveness in error modeling.

Conclusion: The study concludes that Turbo coding is superior to LDPC coding for 5G OFDM systems based on BER performance. The two-state Markov model, estimated using the Baum-Welch algorithm, accurately represents error processes in coded OFDM systems and aligns well with simulation results.

Recommendations: Given its superior performance, Turbo coding should be preferred for channel coding in 5G networks. Extend simulations to include additional modulation schemes and channel conditions to further validate the Markov model and coding techniques.

Future Research: Explore more complex Markov models or alternative statistical methods to improve error prediction accuracy. Conduct field trials to assess the performance of Turbo-coded OFDM systems in practical 5G deployments.

Author's Disclaimers: The results are based on simulated data and may not fully capture real-world channel conditions and network complexities. The accuracy of the Baum-Welch algorithm's parameter estimation depends on convergence criteria and may vary with different iterations. These findings underscore the effectiveness of advanced coding techniques and error modeling in enhancing the performance of 5G OFDM systems.

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