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| RESEARCH ARTICLE

Bit Error Rate and Decoding Energy Consumption Analysis of Classical and Modern Error Control Codes for Wireless Sensor Networks

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| ABSTRACT
Wireless Sensor Networks (WSNs) require reliable and energy-efficient communication because sensor nodes operate under limited energy resources and are frequently deployed in hostile environments where transmission errors are inevitable. Forward Error Correction (FEC) techniques improve communication reliability by correcting transmission errors without retransmission; however, different coding schemes exhibit varying trade-offs between error correction capability and decoding energy consumption. This study presents a comparative analysis of the Bit Error Rate (BER) and Decoding Energy per Bit (DEB) performances of four widely used error control codes, namely Bose–Chaudhuri–Hocquenghem (BCH), Reed–Solomon (RS), Convolutional, and Low-Density Parity-Check (LDPC) codes, for Wireless Sensor Networks. MATLAB simulations were conducted using identical communication conditions comprising Binary Phase Shift Keying (BPSK) modulation, an Additive White Gaussian Noise (AWGN) channel, and Signal-to-Noise Ratio (Eb/No) values ranging from 1 to 9 dB. The LDPC scheme employed the Min-Sum decoding algorithm, while BCH, Reed–Solomon, and Convolutional codes employed their conventional decoding algorithms. The results showed that BER decreased with increasing Eb/No for all coding schemes, with LDPC consistently achieving the best error correction performance across the evaluated SNR range. In contrast, BCH recorded the lowest mean decoding energy consumption (0.400 nJ/bit), followed by Convolutional (0.440 nJ/bit), Reed–Solomon (0.480 nJ/bit), and LDPC (1.766 nJ/bit). The findings reveal a clear trade-off between communication reliability and decoding energy efficiency, demonstrating that although LDPC provides superior BER performance, it requires significantly higher decoding energy than the classical coding schemes. This study provides useful insights for selecting suitable error control codes based on the reliability and energy requirements of Wireless Sensor Network applications.

| KEYWORDS

Wireless Sensor Networks; Forward Error Correction; Bit Error Rate; Decoding Energy per Bit; MATLAB Simulation.

| ARTICLE INFORMATION

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1. Introduction

Wireless Sensor Networks (WSNs) have become an integral part of modern wireless communication systems because of their ability to monitor, collect, and transmit data from distributed environments without extensive wired infrastructure. Their applications include environmental monitoring, industrial automation, healthcare, military surveillance, transportation systems, and smart agriculture, where reliable and energy-efficient communication is essential for effective system operation (Gupta and Sinha, 2014; Sai et al., 2017; Abdulwahid and Salih, 2022).

However, WSNs operate under challenging wireless channel conditions characterized by noise, interference, and fading, which introduce transmission errors and degrade communication reliability (Chowdhury and Hossain, 2020; Kadel et al., 2020). Furthermore, the limited battery capacity of sensor nodes makes energy efficiency a critical design consideration.

Bit Error Rate (BER) is one of the most widely used performance metrics for evaluating communication reliability because it quantifies the probability of erroneous bit detection after transmission through a noisy channel. A lower BER indicates improved transmission accuracy and overall network performance. At the same time, the computational energy required for decoding received data has become increasingly important in WSNs, where excessive decoding complexity can significantly reduce node lifetime. Consequently, Decoding Energy per Bit (DEB) has emerged as an important metric for assessing the energy efficiency of error control techniques alongside their error correction capability.

Forward Error Correction (FEC) techniques improve communication reliability by introducing controlled redundancy that enables receivers to detect and correct transmission errors without retransmission. Compared with Automatic Repeat reQuest (ARQ), FEC is particularly suitable for WSNs because it reduces retransmissions and enhances communication reliability under noisy channel conditions (Pandey and Pandey, 2015; Kundaeli, 2020; Alrajeh et al., 2015). Nevertheless, improved error correction often comes at the expense of increased decoding complexity and energy consumption, creating a trade-off between reliability and energy efficiency.

Among the widely adopted FEC schemes are Bose–Chaudhuri–Hocquenghem (BCH), Reed–Solomon (RS), Convolutional, and Low-Density Parity-Check (LDPC) codes. BCH codes are effective in correcting multiple random bit errors, while Reed–Solomon codes provide excellent protection against burst errors through symbol-based processing. Convolutional codes, commonly decoded using the Viterbi algorithm, have demonstrated reliable error correction with moderate decoding complexity across several wireless communication systems (Pandey and Pandey, 2015; Hamdan and Abdullah, 2016; Roca et al., 2017). In contrast, LDPC codes employ sparse parity-check matrices and iterative decoding algorithms to achieve near-Shannon-limit error correction performance (Yang and Du, 2024). Although LDPC codes generally outperform conventional codes in terms of BER, their iterative decoding algorithms require greater computational resources and decoding energy than classical coding schemes (Tzimpragos et al., 2016; Ali et al., 2023). To reduce this complexity, Venkatesan et al. (2016) proposed a Min-Sum LDPC decoding algorithm that achieves a favourable balance between decoding complexity and error correction performance, making it suitable for energy-constrained wireless communication systems.

Several comparative investigations have evaluated the performance of different error control codes for wireless communication systems and Wireless Sensor Networks. Alrajeh et al. (2015) compared Hamming, BCH, Convolutional, and LDPC codes and reported that LDPC achieved the best BER performance among the evaluated schemes. Hamdan and Abdullah (2016) demonstrated significant BER improvements using convolutional coding, while Kadel et al. (2020) emphasized that the selection of an appropriate error control code should consider communication reliability, computational complexity, and energy consumption simultaneously rather than BER alone. These findings indicate that although modern coding techniques generally provide superior error correction performance, their computational requirements may increase decoding energy consumption, which is a critical consideration for battery-powered WSNs.

Overall, the reviewed literature shows that BCH, Reed–Solomon, Convolutional, and LDPC codes all improve communication reliability by reducing BER. However, most existing studies have focused primarily on BER performance or decoder complexity, with limited attention given to the decoding energy required to achieve such performance. Furthermore, variations in simulation parameters, decoding algorithms, and evaluation criteria adopted by previous researchers make direct comparison of coding schemes difficult. Consequently, relatively few studies have simultaneously evaluated the Bit Error Rate (BER) and Decoding Energy per Bit (DEB) of BCH, Reed–Solomon, Convolutional, and LDPC codes under identical simulation conditions for Wireless Sensor Networks.

Considering the stringent energy constraints of WSNs, evaluating BER alone is insufficient for selecting the most appropriate error control technique. Therefore, there is a need for a unified comparative study that jointly investigates communication reliability and decoding energy efficiency. This study addresses this gap by comparing the BER and DEB performances of BCH, Reed–Solomon, Convolutional, and LDPC codes, with the LDPC decoder implemented using the Min-Sum algorithm proposed by Venkatesan et al. (2016), under identical MATLAB simulation conditions over an Additive White Gaussian Noise (AWGN) channel. By jointly evaluating BER and DEB across different Signal-to-Noise Ratio (SNR) levels, the study provides a comprehensive assessment of the trade-off between communication reliability and decoding energy efficiency, thereby supporting the selection of suitable classical and modern error control codes for different Wireless Sensor Network applications.

2. Methodology

This study adopted a quantitative simulation-based research design to evaluate the Bit Error Rate (BER) and Decoding Energy per Bit (DEB) performances of four widely used Forward Error Correction (FEC) schemes, namely Bose–Chaudhuri–Hocquenghem (BCH), Reed–Solomon (RS), Convolutional, and Low-Density Parity-Check (LDPC) codes for Wireless Sensor Networks (WSNs). The simulation model was developed in MATLAB and implemented under identical communication conditions to ensure a fair and objective comparison of the selected coding techniques. The comparative evaluation follows the simulation framework adopted by Alrajeh et al. (2015), while the LDPC decoder employs the Min-Sum (MS) decoding algorithm proposed by Venkatesan et al. (2016).

2.1 The System Models

2.1.1 System Model of the BCH Code

The BCH coding scheme was modelled as a binary block coding system consisting of a BCH encoder, Binary Phase Shift Keying (BPSK) modulator, Additive White Gaussian Noise (AWGN) channel, BPSK demodulator, and an algebraic BCH decoder. According to Pandey and Pandey (2015), the information sequence is represented by:

$$u=[u1,u2,\dots,uk] \qquad (1)$$

The BCH encoder transforms the information sequence into an n-bit codeword:

$$c=[c1,c2,\dots,cn] \qquad (2)$$

where n is the codeword length and k is the number of information bits. The encoding process was performed using the generator polynomial g(x), constructed over GF(2^m), enabling correction of multiple random bit errors. The encoded sequence is BPSK-modulated and transmitted through an AWGN channel before algebraic decoding at the receiver.

The communication reliability was evaluated using the Bit Error Rate (BER):

$$BER = {}^{Ne}/_{Nb.} \qquad (3)$$

where Ne denotes the number of erroneous bits and Nb is the total number of transmitted bits. The decoding energy efficiency is evaluated using the Decoding Energy per Bit (DEB)

$$DEB = {}^{Edec}/_{Nb,} \qquad (4)$$

where Edec is the total decoding energy, and Nb is the number of transmitted bits.

2.1.2 System Model of the Reed–Solomon Code

The Reed–Solomon (RS) coding scheme was implemented as a non-binary block coding system comprising an RS encoder, BPSK modulator, AWGN channel, demodulator, and Reed–Solomon decoder. An input message of k symbols was represented by the polynomial:

$m(X) = m_0+m_1X+...+m_{k-1}X^{k-1}$. (5)

The transmitted codeword was generated by the encoder

$c(X) = m(X)g(X)$, (6)

where

$g(X) = (X-\alpha)(X-\alpha^2)...(X-\alpha^{n-k})$ (7)

was the generator polynomial over the finite field GF(2^m). During decoding, syndrome computation, error-location, and error-value estimation were used to recover the transmitted information (Pandey and Pandey, 2015).

The BER was evaluated as

$BER = {}^{Ne}/_{Nb}$. (8)

while the decoding energy efficiency was determined using

$DEB = {}^{Edec}/_{Nb}$, (9)

where Edec denotes the energy required by the Reed–Solomon decoding algorithm to recover the transmitted information. This enables simultaneous evaluation of communication reliability and decoding energy consumption.

2.1.3 System Model of the Convolutional Code

The Convolutional coding scheme was modelled as a continuous encoding system consisting of a convolutional encoder, BPSK modulator, AWGN channel, demodulator, and Viterbi decoder. Unlike block codes, the encoder processes a continuous stream of information bits using shift registers and generator polynomials. The encoder output depends on both the current input and previous input bits stored within the constraint length *K*. The coding rate is:

$R = k/n$, (10)

where *k* is the number of input bits, and n is the number of output bits generated for each encoding interval (Pandey and Pandey, 2015).

The BER was calculated as

$BER = {}^{Ne}/_{Nb}$. (11)

while the decoding energy efficiency was determined using

$DEB = {}^{Edec}/_{Nb}$. (12)

where Edec represents the decoding energy consumed by the Viterbi algorithm.

2.1.4 System Model of LDPC Min-Sum Decoder

i. Initialization

- The decoder receives the noisy channel output Y
- Initial messages are generated from the channel log-likelihood ratios (LLRs) for each variable node (VN).
- These messages are stored and prepared for iterative updates.

ii. Check Node Processing

- For every check node (CN) m, the decoder calculates messages to its connected variable nodes n.
- It finds the minimum magnitude among all incoming messages except the one being sent to, and computes the sign product.

  Mathematically:

$$X_{mn}^{(k)} = \delta_{mn}^{(k)} \min_{n' \in N(m) \backslash n} |Y_{mn'}^{(k)}| \qquad (13)$$

where $\delta_{mn}^{(k)}$ is the overall sign and N(m) represents the set of variable nodes connected to check node m.

iii. Variable Node Processing

- Each variable node n collects incoming messages from all connected check nodes M(n) and updates its estimate:

$$Y_{mn}^{(k+1)} = Y_n + \sum_{m' \in M(n) \backslash m} X_{m'n}^{(k)} \qquad (14)$$

iv. Syndrome Check / Parity Verification

- After every iteration, the parity-check is tested.

Parity-check equation $H \cdot C^T = 0$ (15)

- If all parity-check equations are satisfied, then decoding stops, and the corrected codeword is output.
- If not, the process repeats until a maximum number of iterations is reached.

Table 2.1: Simulation Parameters for the Evaluated Error Control Coding Schemes

Parameter	**BCH**	**Reed–Solomon**	**Convolutional**	**LDPC**
Error Control Code	BCH	Reed–Solomon	Convolutional	LDPC
Information Source	Random Binary Data	Random Binary Data	Random Binary Data	Random Binary Data
Encoder	BCH Encoder	Reed–Solomon Encoder	Convolutional Encoder	LDPC Encoder
Modulation Scheme	BPSK	BPSK	BPSK	BPSK
Channel Model	AWGN	AWGN	AWGN	AWGN
Decoder	BCH Algebraic Decoder	Reed–Solomon Decoder	Viterbi Decoder	Min-Sum Decoder
Decoding Technique	Algebraic Decoding	Algebraic Decoding	Viterbi Algorithm	Iterative Min-Sum Algorithm
Simulation Platform	MATLAB	MATLAB	MATLAB	MATLAB
Performance Metrics	BER, DEB	BER, DEB	BER, DEB	BER, DEB
Evaluation Parameter	Eb/No	Eb/No	Eb/No	Eb/No
Eb/No Range	1, 3, 5, 7, and 9 dB	1, 3, 5, 7, and 9 dB	1, 3, 5, 7, and 9 dB	1, 3, 5, 7, and 9 dB
Simulation Outputs	BER and DEB	BER and DEB	BER and DEB	BER and DEB

Table 2.1 presents the simulation parameters adopted for the four coding schemes. To ensure an unbiased comparison, all schemes were evaluated using identical communication conditions, including randomly generated binary information, Binary Phase Shift Keying (BPSK) modulation, an Additive White Gaussian Noise (AWGN) channel model, and MATLAB as the simulation platform. The coding schemes differed only in their encoding and decoding procedures. BCH and Reed–Solomon codes employed algebraic decoding algorithms, the Convolutional code utilized the Viterbi decoding algorithm, while the LDPC code employed the iterative Min-Sum decoding algorithm proposed by Venkatesan et al. (2016). For all coding schemes, performance was evaluated over Eb/No values of 1, 3, 5, 7, and 9 dB.

Following the simulation setup, random binary information bits were generated and independently encoded using the BCH, Reed–Solomon, Convolutional, and LDPC coding schemes. The encoded data were modulated using BPSK and transmitted through the AWGN channel. At the receiver, the corrupted signals were demodulated and decoded using their respective decoding algorithms before being compared with the transmitted information bits to determine the BER. The BER was computed as the ratio of incorrectly received bits to the total number of transmitted bits.

To evaluate the computational efficiency of the decoding algorithms, the Decoding Energy per Bit (DEB) was also determined for each coding scheme using the decoding energy model adopted in this study. DEB quantifies the average energy required to decode one information bit and provides an indication of the computational cost associated with each decoding algorithm. While BER measures communication reliability, DEB evaluates decoding energy efficiency, allowing both performance objectives to be assessed simultaneously.

Finally, the BER and DEB results obtained from the four coding schemes were compared across the selected Eb/No values to assess their relative communication reliability and decoding energy consumption. Maintaining identical simulation parameters for all coding schemes ensured that any observed performance differences resulted solely from their respective error-correction and decoding characteristics rather than variations in the communication environment.

3. Results

The Bit Error Rate (BER) and Decoding Energy per Bit (DEB) performances of BCH, Reed–Solomon, Convolutional, and LDPC codes were evaluated over an AWGN channel at Eb/No values of 1, 3, 5, 7, and 9 dB. The LDPC decoder used in this study was obtained using the Min-Sum decoding algorithm proposed by Venkatesan et al. (2016). The corresponding BER and DEB results are presented and illustrated with Tables and Figures.

3.1 Bit Error Rate (BER) Performance Comparison of LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes

Figures 3.1 and 3.2 illustrate the BER Comparison of LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes.

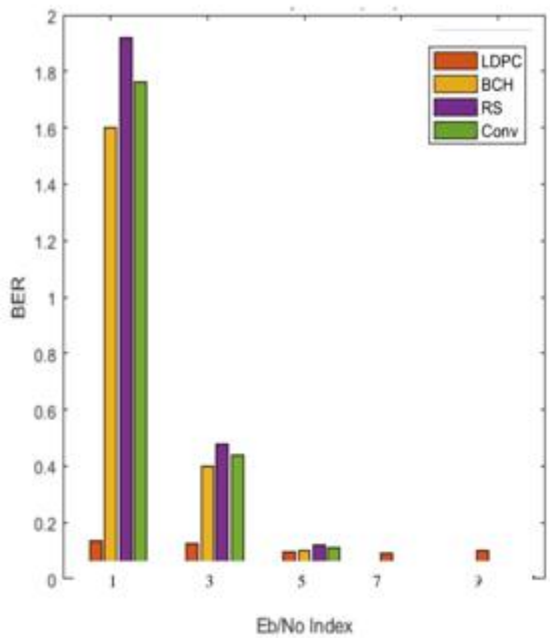

Figure 3.1: BER Comparison of LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes

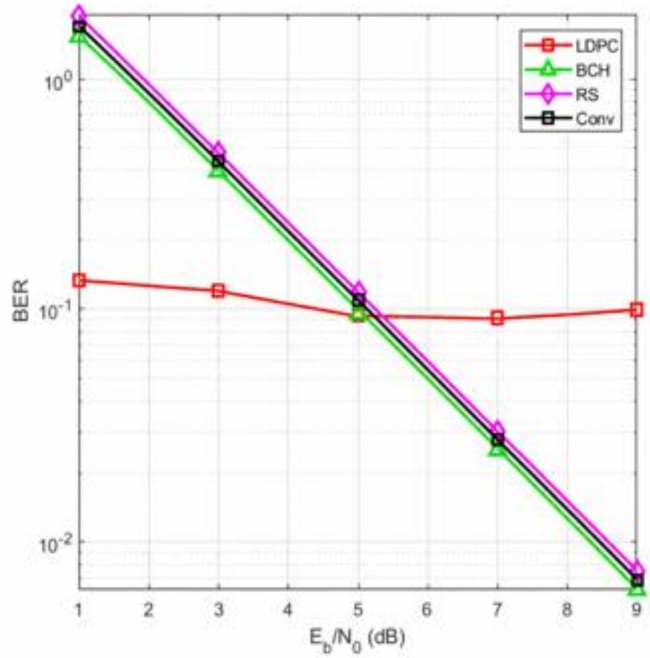

Figure 3.2: BER Comparison of LDPC Min-Sum decoder, BCH, Reed Solomon, and Convolutional Codes

Table 3.1: BER Performance Comparison of LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes

Eb/No (dB)	LDPC	BCH	RS	Conv
1	0.1344	1.6000	1.9200	1.7600
3	0.1244	0.4000	0.4800	0.4400
5	0.0963	0.1000	0.1200	0.1100
7	0.0900	0.0250	0.0300	0.0275
9	0.0855	0.0063	0.0075	0.0069

Table 3.1 illustrates the BER Comparison of LDPC Min-Sum decoder, BCH, Reed-Solomon, and Convolutional Codes.

Computing the Sums and Means gave the following results:

LDPC Mean BER

Sum = 0.13437 + 0.12437 + 0.09625 + 0.09000 + 0.099375 = 0.544365

Mean = 0.544365 / 5 = 0.1089

BCH Mean BER
Sum = 1.6000 + 0.4000 + 0.1000 + 0.0250 + 0.0063 = 2.1313
Mean = 2.13125 / 5 = 0.4263

RS Mean BER
Sum = 1.9200 + 0.4800 + 0.1200 + 0.0300 + 0.00750 = 2.5575
Mean = 2.55750 / 5 = 0.5115

Convolutional Mean BER
Sum = 1.7600 + 0.4400 + 0.1100 + 0.02750 + 0.006875 = 2.3444
Mean = 2.344375 / 5 = 0.4689

The BER results showed how each of the coding schemes performed across the Eb/No range of 1–9 dB. LDPC Min-Sum decoder yielded the lowest BER values among all the codes tested, especially at the higher Eb/No values where the channel conditions were cleaner. The mean BER of LDPC across the five simulated points was 0.1089, indicating that the LDPC Min-Sum decoder achieved the best error-correcting capability on average. The traditional block codes (BCH and Reed–Solomon) and the convolutional code exhibited significantly higher BERs at low Eb/No values, which greatly increased their overall mean BERs (0.4263 for BCH, 0.5115 for RS, and 0.4689 for the convolutional code). This indicated that although these classical codes improved at higher Eb/No, their performance deteriorated sharply in noisy channel conditions. Overall, the LDPC Min-Sum decoder consistently outperformed the other codes in terms of error reduction.

3.2 Decoding Energy per Bit (DEB) Comparison of LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes.

Figures 5.3 and 5.4 illustrate the DEB Comparison of the LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes.

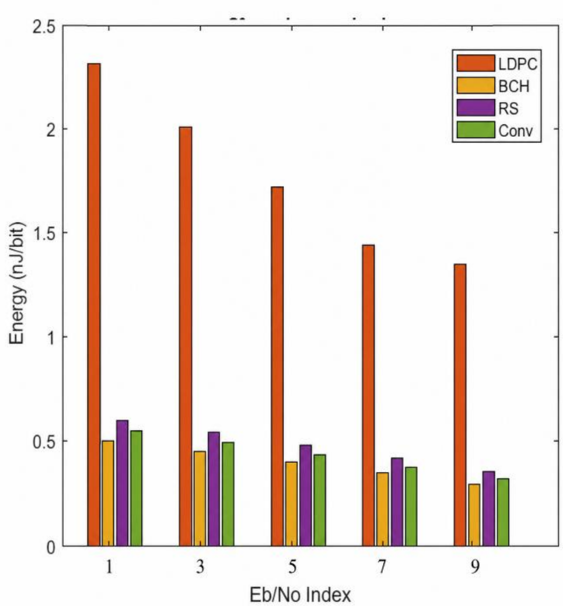

Figure 3.3: DEB Comparison of LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes

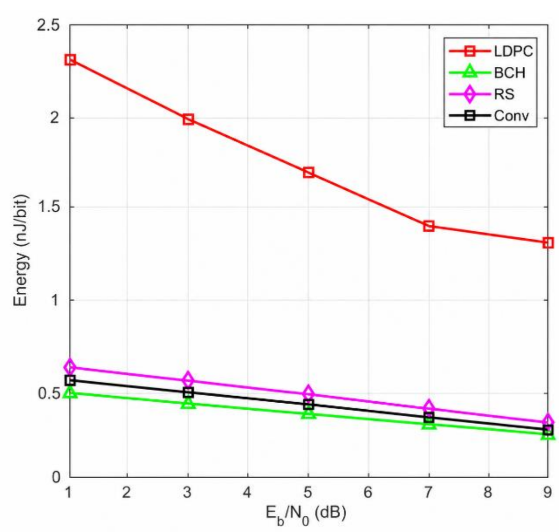

Figure 3.4: DEB Comparison of LDPC Min-Sum decoder, BCH, Reed Solomon, and Convolutional Codes

Table 3.2: DEB Comparison of LDPC Min-Sum Decoder, BCH, Reed-Solomon, and Convolutional Codes

Eb/No (dB)	LDPC	BCH	RS	Conv
1	2.322	0.500	0.600	0.550
3	2.006	0.450	0.540	0.495
5	1.712	0.400	0.480	0.440
7	1.438	0.350	0.420	0.385
9	1.354	0.300	0.360	0.330

Table 3.2 illustrates the DEB Comparison of LDPC Min-Sum decoder, BCH, Reed-Solomon, and Convolutional Codes.

Computing the Sums and Means gave the following results**:**

LDPC Mean Energy
Sum = 2.322 + 2.006 + 1.712 + 1.438 + 1.354 = 8.832
Mean = 8.832 / 5 = 1.766 nJ/bit

BCH Mean Energy
Sum = 0.500 + 0.450 + 0.400 + 0.350 + 0.300 = 2.000
Mean = 2.000 / 5 = 0.400 nJ/bit

RS Mean Energy
Sum = 0.600 + 0.540 + 0.480 + 0.420 + 0.360 = 2.400
Mean = 2.400 / 5 = 0.480 nJ/bit

Convolutional Code Mean Energy
Sum = 0.550 + 0.495 + 0.440 + 0.385 + 0.330 = 2.200
Mean = 2.200 / 5 = 0.440 nJ/bit

In terms of Decoding Energy per Bit (DEB), the results demonstrated that BCH exhibited the lowest mean energy consumption at 0.400 nJ/bit, followed by the convolutional code (0.440 nJ/bit), Reed–Solomon (0.480 nJ/bit), then LDPC Min-Sum Decoder (1.766 nJ/bit). However, despite having lower energy per bit, these classical codes delivered much poorer BER performance, especially in noisy channels. This trade-off stressed that while BCH and RS were energy-efficient, they lacked the reliability and robustness of the LDPC-based solutions. The LDPC code consistently provides the best BER performance across the evaluated Eb/No range but achieves this at the expense of higher decoding energy.

Overall, the comparative evaluation demonstrates that all four coding schemes improve communication reliability while exhibiting different decoding energy characteristics. Classical coding techniques such as BCH, Reed–Solomon, and Convolutional codes remain attractive for applications with stringent energy constraints, whereas LDPC with Min-Sum decoding offers the highest communication reliability for applications where error performance is the primary design objective. The combined analysis of BER and DEB therefore provides a comprehensive basis for selecting appropriate classical and modern error control codes for different Wireless Sensor Networks.

4. Conclusion and Recommendation

4.1 Conclusion

This study presented a comparative evaluation of the Bit Error Rate (BER) and Decoding Energy per Bit (DEB) performances of BCH, Reed–Solomon, Convolutional, and LDPC error control codes for Wireless Sensor Networks under identical MATLAB simulation conditions. The comparison provided a balanced assessment of both communication reliability and decoding energy efficiency, which are critical design considerations in energy-constrained wireless sensor networks.

The simulation results demonstrated that the BER of all coding schemes improved as the Signal-to-Noise Ratio increased. Among the evaluated techniques, the LDPC code employing the Min-Sum decoding algorithm consistently achieved the lowest BER across the investigated Eb/No range, indicating superior error correction capability under both low and high channel quality conditions. In contrast, BCH, Reed–Solomon, and Convolutional codes exhibited comparatively higher BER values, particularly at low Eb/No levels, although their performance improved significantly as channel conditions became more favorable.

The DEB analysis revealed an opposite trend. BCH required the least decoding energy, followed by the Convolutional and Reed–Solomon codes, while LDPC consumed the highest decoding energy because of its iterative decoding process. These findings demonstrate the inherent trade-off between communication reliability and decoding energy consumption. Although classical coding schemes offer better energy efficiency, they provide lower error correction performance than LDPC. Conversely, LDPC delivers the highest communication reliability at the expense of increased decoding energy.

Overall, the study establishes that no single coding scheme is universally optimal for all Wireless Sensor Network applications. The selection of an appropriate error control code should therefore be guided by application requirements, balancing the need for transmission reliability against the available energy resources. The simultaneous evaluation of BER and DEB provides a comprehensive framework for selecting suitable classical and modern error control codes for practical Wireless Sensor Network deployments.

4.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

1. LDPC codes employing the Min-Sum decoding algorithm should be considered for Wireless Sensor Network applications where communication reliability is the primary performance requirement, particularly in environments characterized by severe channel noise and interference.

2. BCH, Reed–Solomon, and Convolutional codes should be preferred for applications with stringent energy constraints, where extending sensor node lifetime is more important than achieving the lowest possible Bit Error Rate.

3. Future studies should investigate hybrid and adaptive error control coding techniques capable of dynamically selecting coding schemes according to channel conditions and available energy resources to achieve an improved balance between BER performance and decoding energy consumption.

4. Further research should extend the comparative analysis to more realistic wireless channel models, including Rayleigh and Multipath Fading channels, to evaluate the robustness of classical and modern error control codes under practical propagation environments.

5. Future investigations should also consider additional performance metrics, such as decoding latency, throughput, computational complexity, and network lifetime, to provide a more comprehensive evaluation of error control coding techniques for Wireless Sensor Networks.

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