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## | RESEARCH ARTICLE

### Trade-off Analysis of Reliability and Energy Efficiency in SPA and MSA LDPC Decoding Algorithms for Wireless Sensor Networks

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#### | ABSTRACT

Low-Density Parity-Check (LDPC) codes provide strong error-correction capability for wireless communication systems, but their iterative decoding process introduces computational and energy costs that are particularly important in energy-constrained Wireless Sensor Networks (WSNs). This study comparatively evaluates the Sum-Product Algorithm (SPA) and the Min-Sum Algorithm (MSA) for LDPC decoding, with emphasis on the trade-off between communication reliability and estimated decoding energy. A simulation-based evaluation was implemented in MATLAB R2019b using BPSK modulation over an Additive White Gaussian Noise (AWGN) channel. Both decoders were evaluated under identical conditions over  $E_b/N_0$  values of 1–9 dB using Bit Error Rate (BER), average decoding iterations, and estimated Decoding Energy per Bit (DEB) as performance measures. SPA achieved a lower mean BER of 0.00528, compared with 0.00956 for MSA. Conversely, MSA required fewer average decoding iterations (8.6 versus 10.8) and consequently achieved a lower mean estimated DEB of 0.43 nJ/bit compared with 0.54 nJ/bit for SPA under the adopted common fixed energy-per-iteration model. The results demonstrate a clear reliability–energy trade-off: SPA provides higher decoding reliability, whereas MSA reduces iterative computational effort and estimated decoding energy. MSA therefore represents a practical alternative for energy-constrained WSN applications where a moderate reliability penalty can be tolerated.

#### | KEYWORDS

Low-Density Parity-Check (LDPC) codes; Sum-Product Algorithm (SPA); Min-Sum Algorithm (MSA); Wireless Sensor Networks (WSNs); Bit Error Rate (BER); Decoding Energy per Bit (DEB).

#### | ARTICLE INFORMATION

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#### 1. Introduction

Wireless Sensor Networks (WSNs) have emerged as important enabling technologies for modern wireless communication and Internet of Things (IoT) systems. Their ability to sense, process, and transmit information from distributed physical environments has supported applications including environmental monitoring, healthcare, industrial automation, agriculture, surveillance, structural health monitoring, transportation, and IoT systems (Akyildiz et al., 2002; Sai et al., 2017; Kamal & Salahuddin, 2015; Kandris et al., 2020; Fu et al., 2023; Kadel et al., 2020; Chowdhury & Hossain, 2020; Nourilidean et al., 2022). A typical WSN consists of distributed sensor nodes that

collect information and transmit it to a sink node or base station. Because these nodes are commonly battery powered and have constrained processing, memory, communication, and energy resources, energy conservation remains a central design consideration (Abdulwahid & Salih, 2021; BenSaleh et al., 2020; Chowdhury & Hossain, 2020).

Wireless communication is inherently vulnerable to noise and other channel impairments that can corrupt transmitted information and reduce communication reliability (Arora et al., 2016; Xu et al., 2022; Eghonghon et al., 2020). Error-control mechanisms are therefore essential for maintaining reliable data delivery. Automatic Repeat reQuest (ARQ) can recover corrupted packets through retransmission but may increase latency, bandwidth use, and energy consumption when channel conditions are poor. Hybrid ARQ (HARQ) combines Forward Error Correction (FEC) with retransmission and consequently introduces additional processing and communication overhead (Kundaeli, 2020; Goyal et al., 2018). FEC provides an alternative by adding controlled redundancy that allows the receiver to detect and correct errors without requiring retransmission, thereby improving reliability and potentially reducing retransmission-related energy expenditure (Ali et al., 2023; Spyrou & Kappatos, 2022; Goyal et al., 2018).

However, FEC does not eliminate energy consumption; rather, it can transfer part of the energy cost from transmission and retransmission to encoding and decoding operations. The selection of an error-correcting code therefore involves a trade-off among error-correction capability, computational complexity, decoding energy, and reliability (Alrajeh et al., 2015; Kadel et al., 2020; Ali et al., 2023; Joshi & Kulkarni, 2018). Conventional BCH, Reed-Solomon, and convolutional codes remain important coding techniques (Pandey & Pandey, 2015; Roca et al., 2017), but LDPC codes have gained particular attention because of their strong error-correction capability and sparse parity-check structure (Yang & Du, 2024; Ali et al., 2023; Sudha Kumari et al., 2022). LDPC codes are consequently used in a wide range of communication applications.

The principal limitation of LDPC codes in energy-constrained systems is the iterative nature of their decoding process. LDPC decoding repeatedly exchanges soft reliability information between variable and check nodes until the parity-check constraints are satisfied or a maximum iteration limit is reached. Increasing the number of iterations generally increases computational workload, memory access, latency, and decoder energy requirements (Alrajeh et al., 2015; Kadel et al., 2020; Chowdhury & Hossain, 2020; Rudraunsh et al., 2024). Consequently, decoder selection and optimization are important in WSNs, where excessive computational energy can reduce the useful lifetime of sensor nodes (Joshi & Kulkarni, 2018; Singh et al., 2020).

The Sum-Product Algorithm (SPA) is a conventional belief-propagation approach that uses soft probabilistic information to perform iterative LDPC decoding. It provides strong error-correction performance but requires computationally intensive nonlinear operations, including hyperbolic-tangent and inverse-hyperbolic-tangent calculations. The Min-Sum Algorithm (MSA) provides a lower-complexity approximation by replacing these operations at the check nodes with sign and minimum-magnitude operations. Low-complexity and hardware-oriented decoding architectures have been investigated for convolutional and other error-control codes (Hamdan & Abdullah, 2016; Putra & Adiono, 2016), while Min-Sum-based LDPC implementations have demonstrated the potential for reduced complexity and power consumption (Venkatesan et al., 2016; Rudraunsh et al., 2024). These developments provide the hardware-efficiency context for the SPA/MSA comparison undertaken in this study.

Previous research has established the energy implications of LDPC and other error-control decoding. Alrajeh et al. (2015) compared classical and modern error-correcting codes from an energy perspective and reported that LDPC can provide strong error-correction performance while imposing comparatively high decoding-energy requirements. Reviews of WSN error-control schemes have likewise emphasized the need to balance reliability, coding overhead, energy consumption, and channel conditions (Kadel et al., 2020; Ali et al., 2023). Venkatesan et al. (2016) demonstrated the low-power potential of Min-Sum decoding through hardware implementation, while Magzoub et al. (2020) examined energy efficiency across error-correcting codes in WSNs. Onyeonwu et al. (2026) investigated an energy-efficient Layered Min-Sum LDPC decoder with Early Stopping under AWGN, showing how iteration reduction can lower estimated decoding energy.

Despite these developments, the literature considered here does not provide a direct, controlled SPA-versus-conventional-MSA comparison in which the two decoders are subjected to the same LDPC code, BPSK/AWGN conditions, simulation duration, stopping rule, and performance measures while reliability and iteration-based decoding energy are evaluated jointly. Prior studies have generally focused on broader WSN error-control surveys, comparisons among different code families, low-power Min-Sum hardware implementations, or optimized Layered Min-Sum/early-stopping approaches (Alrajeh et al., 2015; Kadel et al., 2020; Venkatesan et al., 2016; Magzoub et al., 2020; Onyeonwu et al., 2026). What remains less explicit is the practical trade-off between the reliability advantage of full SPA message passing and the iteration/energy advantage of conventional MSA when both are evaluated under otherwise identical conditions.

Accordingly, the contribution of the present study is threefold. First, it provides a controlled head-to-head evaluation of SPA and conventional MSA using the same rate-1/2 LDPC (16,8) code, BPSK modulation, AWGN channel, Eb/N0 operating points, simulation length, and convergence rule. Second, it evaluates reliability and computational effort jointly through BER and average decoding iterations and translates the latter into a transparent, model-based Decoding Energy per Bit (DEB) metric. Third, it interprets the resulting reliability–energy trade-off specifically for WSNs, where decoder computation contributes to the limited energy budget of battery-powered nodes. This contribution complements the dissertation's earlier focus on Layered Min-Sum and Early Stopping by isolating the conventional SPA-versus-MSA trade-off under controlled conditions.

## **2. Methodology**

This study adopted a simulation-based comparative research design to investigate the reliability and energy-efficiency trade-off between the Sum-Product Algorithm (SPA) and the Min-Sum Algorithm (MSA) for Low-Density Parity-Check (LDPC) decoding. Both decoders were evaluated under identical communication conditions so that differences in BER, iteration count, and estimated DEB could be attributed to the decoding strategy rather than to differences in modulation, channel, simulation length, or stopping conditions.

The simulation framework was implemented in MATLAB R2019b using Binary Phase Shift Keying (BPSK) modulation over an Additive White Gaussian Noise (AWGN) channel. AWGN was selected as the baseline channel because it provides a controlled environment for evaluating channel-coding performance without the additional effects of multipath fading or shadowing. The SPA and MSA implementations used the same Eb/N0 values, LDPC code, maximum iteration limit of 20 iterations per codeword, syndrome-based stopping criterion, data volume, and simulation stopping conditions. For reproducibility, the MATLAB random-number generator was initialized using the fixed seed 42 with the Mersenne Twister generator (rng(42,'twister')).

### **2.1 System Model**

The simulated communication system comprised binary information generation, LDPC encoding, BPSK modulation, transmission over the AWGN channel, and iterative LDPC decoding using either SPA or MSA. The decoded information sequence was compared with the original information sequence to determine BER. The number of decoding iterations was recorded for each simulation condition and was subsequently used in the adopted iteration-based DEB model.

$b \rightarrow \text{LDPC Encoder} \rightarrow \text{BPSK Modulator} \rightarrow \text{AWGN Channel} \rightarrow \text{LDPC Decoder (SPA/MSA)} \rightarrow \hat{b}$

where  $b$  denotes the transmitted binary information sequence and  $\hat{b}$  denotes the decoded information sequence. Both decoding algorithms received the same soft channel information and used the same maximum iteration and stopping conditions.

### **2.2 LDPC Encoding**

LDPC coding is defined by a sparse parity-check matrix  $H$ . The encoded codeword  $c$  satisfies the parity-check condition:

$$Hc^T = 0 \quad (1)$$

The matrix is explicitly specified in the MATLAB implementation and is used consistently by both decoders for message updates and syndrome verification. The simulation sequence is reproducible because the MATLAB random-number generator is initialized with `rng(42,'twister')`. The same seeded information-bit stream, code structure, channel model, and operating points are used for both decoder evaluations, while only the decoding algorithm is changed.

The study used a rate-1/2 LDPC (16,8) code. The implemented parity-check matrix contains 8 parity-check equations and 16 coded-bit columns, i.e.,  $H$  is an  $8 \times 16$  matrix. The actual matrix used in the MATLAB decoding implementation is shown in Table 1. The corresponding transpose representation is included in Table 2 for dimensional clarity. The codeword  $c$  is valid when it satisfies the parity-check condition  $Hc^T = 0$  over GF (2).

Table 1. Actual  $8 \times 16$  parity-check matrix used in the MATLAB implementation.

| 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

For completeness, the corresponding  $16 \times 8$  transpose representation,  $H^T$ , is shown in Table 2. The  $8 \times 16$  matrix in Table 1 is the actual parity-check matrix used in the decoding equation  $Hc^T = 0$ . The same  $H$  was used for syndrome checking after each decoding iteration.

Table 2. Corresponding  $16 \times 8$  transpose representation,  $H^T$ .

| 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |
| 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 |
| 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |
| 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |

### 2.3 BPSK Modulation

The encoded binary sequence was modulated using BPSK. The binary mapping was defined as:

$$0 \rightarrow +1, \quad 1 \rightarrow -1$$

$$x = 1 - 2b \quad (2)$$

where  $b \in \{0,1\}$  is the binary symbol and  $x$  is the corresponding transmitted BPSK symbol.

#### **2.4 AWGN Channel Model**

The transmission channel was modelled as an Additive White Gaussian Noise channel. The received signal is represented by:

$$y = x + n \quad (3)$$

where  $x$  is the transmitted BPSK symbol,  $y$  is the received symbol, and  $n$  is zero-mean Gaussian noise. The noise was modelled as  $n \sim N(0, \sigma^2)$ , with:

$$\sigma^2 = N_0 / 2 \quad (4)$$

The performance of both decoders was evaluated at  $E_b/N_0$  values of 1, 3, 5, 7, and 9 dB.

#### **2.5 Sum-Product Algorithm (SPA)**

SPA is an iterative belief-propagation decoding method that exchanges soft reliability information between the variable and check nodes of the LDPC Tanner graph. For BPSK transmission over AWGN, the channel Log-Likelihood Ratio (LLR) is obtained as:

$$L_i = 2y_i / \sigma^2 \quad (5)$$

The check-node update is expressed in the conventional belief-propagation form as:

$$L_{i \rightarrow j} = 2 \tanh^{-1} \left[ \prod_{k \in N(i) \setminus \{j\}} \tanh(L_{k \rightarrow i} / 2) \right] \quad (6)$$

The variable-node update is:

$$L_{j \rightarrow i} = L_j + \sum_{k \in N(j) \setminus \{i\}} L_{k \rightarrow j} \quad (7)$$

The iterative process continues until the estimated codeword satisfies the parity-check constraints or the maximum permitted number of iterations is reached. In this study, convergence was tested using the syndrome condition  $H\hat{c}^T \bmod 2 = 0$ . Thus, a codeword was regarded as successfully converged when every parity-check equation was satisfied. If the syndrome remained nonzero, decoding continued until the 20-iteration maximum was reached.

#### **2.6 Min-Sum Algorithm (MSA)**

MSA approximates the check-node operation of SPA by replacing the computationally intensive hyperbolic-tangent and inverse-hyperbolic-tangent calculations with sign and minimum-magnitude operations. The check-node update is expressed as:

$$L_{i \rightarrow j} = \left[ \prod_{k \in N(i) \setminus \{j\}} \text{sign}(L_{k \rightarrow i}) \right] \min_{k \in N(i) \setminus \{j\}} |L_{k \rightarrow i}| \quad (8)$$

The variable-node update and final decision process follow the corresponding message-passing structure. The implementation used in this study follows the hardware-efficient Min-Sum principle described by Venkatesan et al. (2016), in which simplified minimum-value and sign operations reduce decoder complexity and power requirements.

#### **2.7 Performance Evaluation**

##### **2.7.1 Bit Error Rate (BER)**

Communication reliability was evaluated using BER, defined as the ratio of erroneous decoded information bits to the total number of information bits evaluated:

$$\text{BER} = N_e / N_b \quad (9)$$

where  $N_e$  is the number of erroneous information bits and  $N_b$  is the total number of information bits evaluated. Lower BER values indicate better communication reliability.

### 2.7.2 Decoding Energy per Bit (DEB)

The energy analysis was restricted to the computational energy associated with iterative LDPC decoding. Transmission, encoding, and retransmission energies were outside the scope of the present evaluation. The study adopted an iteration-based energy model in which the estimated decoding energy per information bit is proportional to the average number of decoding iterations.

$$\text{DEB} = N_{\text{iter}} E_{\text{iter}} \quad (10)$$

where  $N_{\text{iter}}$  is the average number of decoding iterations and  $E_{\text{iter}}$  is the adopted energy coefficient per information bit per decoding iteration. For the present SPA/MSA simulation:

For the present SPA/MSA research publication,  $E_{\text{iter}} = 0.0500$  nJ/bit/iteration was used as an estimated comparative energy coefficient. This coefficient is a model parameter selected for the current study rather than a direct hardware measurement or a value claimed to have been measured in an earlier study. Applying the same coefficient to SPA and MSA establishes a common energy basis; consequently, differences in estimated DEB arise from differences in the number of iterations rather than from assigning different per-iteration energy costs to the two algorithms.

$$\text{DEB} = 0.0500 N_{\text{iter}} \text{ nJ/bit} \quad (11)$$

### 2.7.3 Decoding Iteration Count

The average number of decoding iterations required for successful decoding was recorded for each  $E_b/N_0$  value and for each algorithm. The iteration count represents the number of complete decoding iterations executed before syndrome-based convergence or termination at the fixed maximum of 20 iterations. Fewer iterations indicate lower iterative computational effort and, under the adopted common energy coefficient, lower estimated DEB.

For each  $E_b/N_0$  operating point, the simulation generates the information-bit stream, forms the LDPC codewords, maps the coded bits to BPSK symbols, adds Gaussian noise, and computes the channel LLRs. Each codeword is then decoded independently by SPA and MSA using the same received soft information. After every complete decoding iteration, the hard decision is tested against  $H$ . If  $H\hat{C}^T \bmod 2 = 0$ , decoding stops immediately; otherwise decoding continues until the 20-iteration limit is reached. The decoded information bits are compared with the original information bits to accumulate BER, while the number of executed iterations is accumulated for the DEB calculation.

## 2.8 Simulation Parameters

The simulations were implemented in MATLAB R2019b using identical communication parameters for SPA and MSA. The principal parameters were: AWGN channel; BPSK modulation; rate-1/2 LDPC (16,8) coding; maximum decoding iterations of 20 per codeword; 5,000 information bits per simulation frame; a maximum of 100 simulation frames/blocks; a maximum accumulated error count of 100 bits; and  $E_b/N_0$  values of 1, 3, 5, 7, and 9 dB. The MATLAB random-number generator was initialized with `rng(42,'twister')` to make the simulation sequence reproducible. BER, average decoding iterations, and estimated DEB were used as the principal performance measures.

The 5,000 information bits per frame and maximum of 100 simulation frames are distinct quantities. The former specifies the information-bit content processed in a simulation frame, whereas the latter defines the maximum number of frames used for statistical accumulation. Both SPA and MSA were evaluated using the same stopping

conditions to ensure that the comparison reflected differences in decoding behaviour rather than differences in simulation duration.

### 3. Results

This section presents the simulation results obtained from the comparative evaluation of the Sum-Product Algorithm (SPA) and the Min-Sum Algorithm (MSA) for Low-Density Parity-Check (LDPC) decoding over an Additive White Gaussian Noise (AWGN) channel. The performance of both decoding algorithms was evaluated using Bit Error Rate (BER), average decoding iterations, and estimated Decoding Energy per Bit (DEB) as the principal performance metrics. The simulations were implemented in MATLAB R2019b using identical system parameters to ensure a fair comparison between the two decoding techniques.

#### 3.1 Bit Error Rate (BER) Performance

Figures 3.1 and 3.2 present the BER performance of the SPA and MSA decoders at different values of  $E_b/N_0$ .

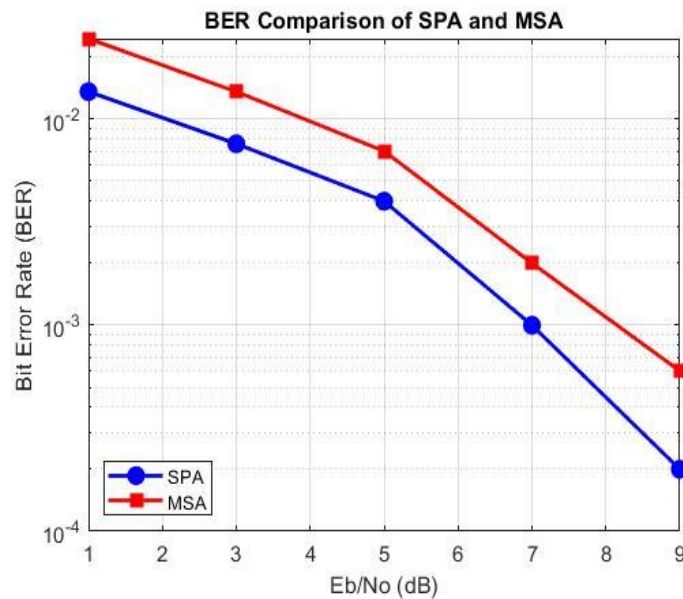


Figure 1. BER vs  $E_b/N_0$  for SPA and MSA

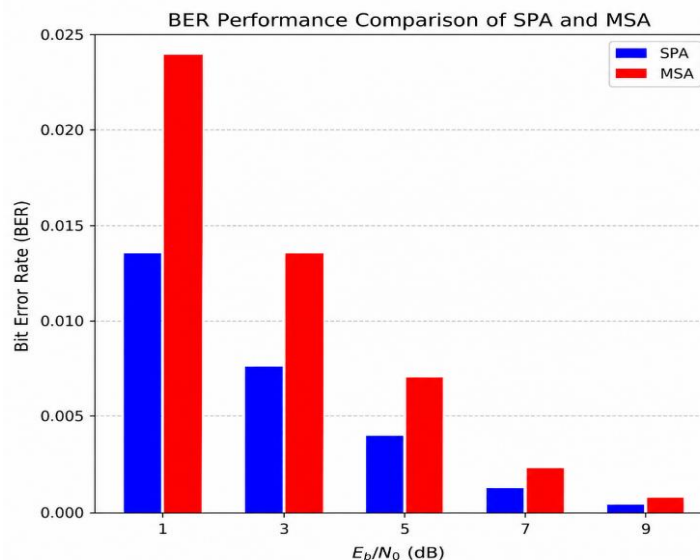


Figure 2. BER vs  $E_b/N_0$  for SPA and MSA

Table 3 presents the BER performance of the SPA and MSA decoders at different values of  $E_b/N_0$ .

| Table 3. BER Comparison of SPA and MSA |         |         |
|----------------------------------------|---------|---------|
| $E_b/N_0$ (dB)                         | SPA BER | MSA BER |
| 1                                      | 0.0136  | 0.0246  |
| 3                                      | 0.0076  | 0.0136  |
| 5                                      | 0.0040  | 0.0070  |
| 7                                      | 0.0010  | 0.0020  |
| 9                                      | 0.0002  | 0.0006  |

The results indicate that both decoding algorithms exhibit improved error-correction capability as the signal-to-noise ratio increases. As the  $E_b/N_0$  value increased from 1 dB to 9 dB, the BER decreased consistently for both algorithms, demonstrating the expected improvement in communication reliability under better channel conditions. However, the Sum-Product Algorithm consistently achieved lower BER values than the Min-Sum Algorithm at every simulated  $E_b/N_0$ . At 1 dB, SPA achieved a BER of 0.0136, whereas MSA recorded 0.0246, representing a noticeably higher error rate for the simplified decoder. Similar trends were observed at 3 dB and 5 dB, where SPA achieved BER values of 0.0076 and 0.0040, compared with 0.0136 and 0.0070 for MSA, respectively.

At higher signal-to-noise ratios, both algorithms produced substantially lower BER values. At 7 dB, SPA reduced the BER to 0.0010, while MSA achieved 0.0020. At the highest simulated  $E_b/N_0$  of 9 dB, SPA achieved the lowest BER of 0.0002, whereas MSA attained 0.0006. These results indicate that although the performance gap between the two algorithms decreases as channel conditions improve, SPA consistently maintains superior decoding accuracy throughout the investigated operating range.

The average BER obtained over all simulated  $E_b/N_0$  values further confirm this observation. SPA achieved an average BER of 0.00528, whereas MSA recorded an average BER of 0.00956. This demonstrates that SPA provides higher communication reliability because its probabilistic message-passing mechanism performs more accurate iterative decoding than the simplified minimum-value approximation employed by MSA.

The observed behavior agrees with the findings of Yang and Du (2024), who reported that SPA achieves superior decoding performance because it utilizes complete probabilistic information during iterative message passing. Similarly, Venkatesan et al. (2016) noted that the simplifications introduced by the Min-Sum Algorithm reduce computational complexity at the expense of a slight degradation in decoding performance.

### 3.2 Decoding Energy per Bit Performance

Figures 3.3 and 3.4 present the decoding energy consumption obtained for both decoding algorithms.

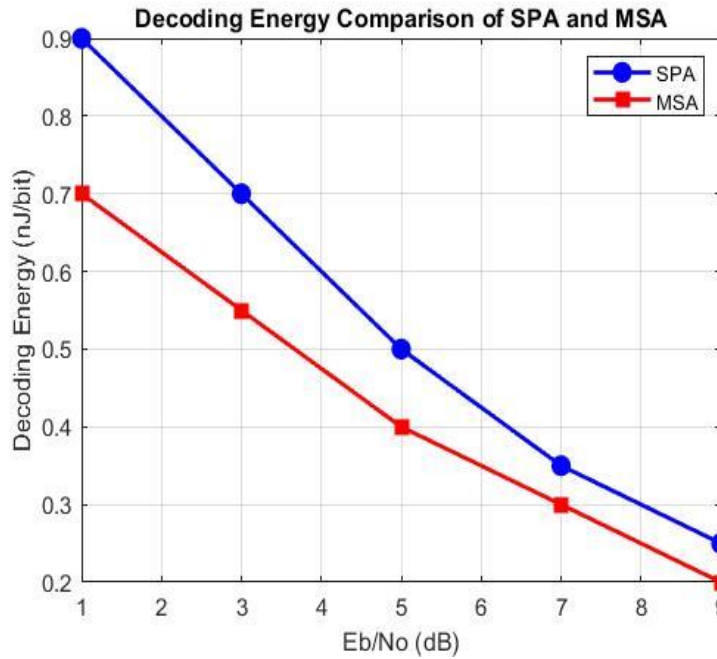


Figure 3. DEB vs Eb/NO for SPA and MSA

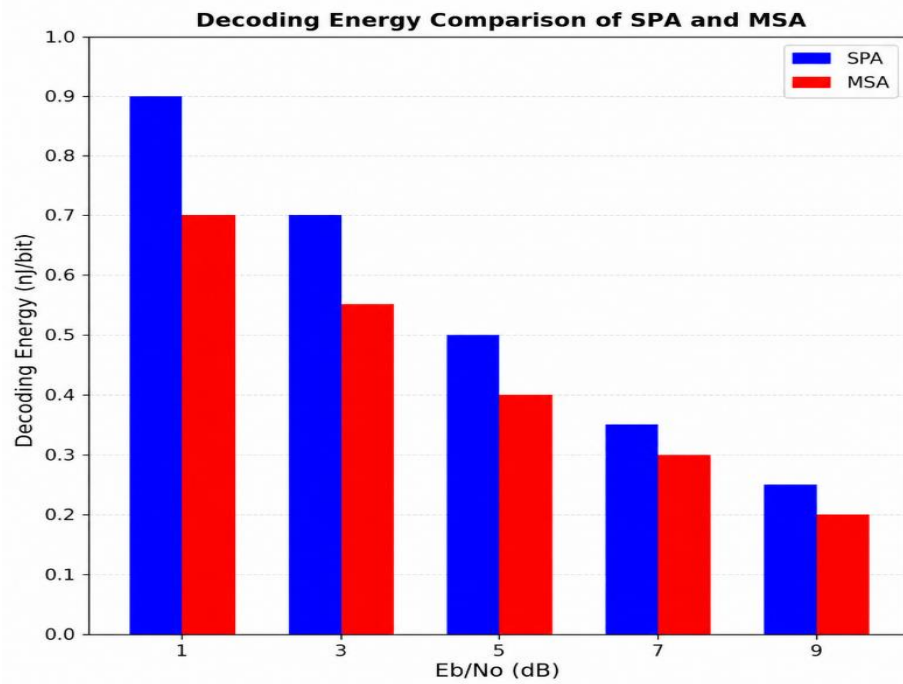


Figure 4. DEB vs Eb/NO for SPA and MSA

Table 4 presents the decoding energy consumption obtained for both decoding algorithms.

| Table 4. Decoding Energy per Bit Comparison |              |              |
|---------------------------------------------|--------------|--------------|
| Eb/No (dB)                                  | SPA (nJ/bit) | MSA (nJ/bit) |
| 1                                           | 0.90         | 0.70         |
| 3                                           | 0.70         | 0.55         |
| 5                                           | 0.50         | 0.40         |
| 7                                           | 0.35         | 0.30         |
| 9                                           | 0.25         | 0.20         |

The simulation results demonstrate that decoding energy consumption decreases progressively as the channel quality improves. This reduction occurs because higher  $E_b/N_0$  values produce fewer transmission errors, allowing successful decoding to be achieved with fewer computational operations.

Across all simulated operating conditions, the Min-Sum Algorithm consistently consumed less decoding energy than the Sum-Product Algorithm. At 1 dB, SPA required 0.90 nJ/bit, whereas MSA required only 0.70 nJ/bit, corresponding to a reduction of approximately 22.2% in decoding energy. Similar reductions were observed throughout the remaining operating range. At 3 dB, decoding energy decreased to 0.70 nJ/bit for SPA and 0.55 nJ/bit for MSA. At 5 dB, the energy requirements further reduced to 0.50 nJ/bit and 0.40 nJ/bit, respectively.

As the channel conditions improved further, the computational energy required by both algorithms continued to decline. At 7 dB, SPA consumed 0.35 nJ/bit, while MSA required 0.30 nJ/bit. At 9 dB, the minimum energy consumption values of 0.25 nJ/bit for SPA and 0.20 nJ/bit for MSA were obtained.

Overall, SPA recorded an average estimated DEB of 0.54 nJ/bit, whereas MSA achieved a lower average estimated DEB of 0.43 nJ/bit. Under the adopted common 0.0500 nJ/bit/iteration coefficient, this difference is explained by MSA's lower average iteration count. The present model does not assign a lower per-iteration energy cost to MSA than to SPA; therefore, the result should be interpreted specifically as an iteration-driven estimated DEB advantage.

The observed energy trend is consistent with Venkatesan et al. (2016), who demonstrated that Min-Sum implementations can reduce decoder complexity and power requirements through simplified sign and minimum-value operations. The present study, however, shows that the estimated DEB advantage of MSA follows from the lower number of iterations under the common fixed energy-per-iteration model.

### 3.3 Decoding Iteration Analysis

Figure 3.5 presents the average number of decoding iterations required by both algorithms under different channel conditions.

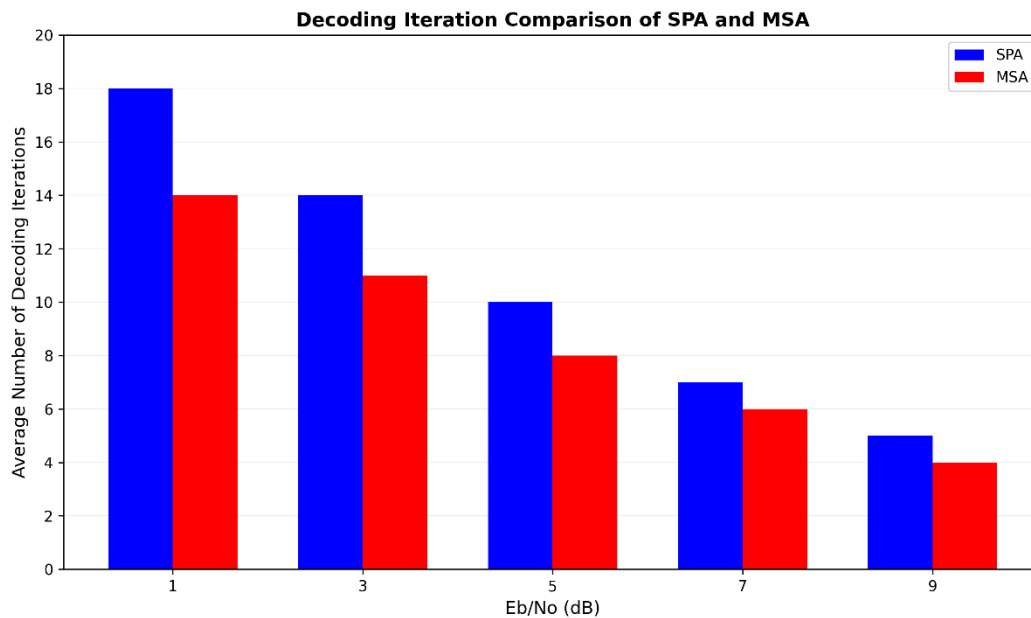


Figure 5. Decoding iteration comparison of the SPA and MSA

Table 5 presents the average number of decoding iterations required by both algorithms under different channel conditions.

Table 5. Decoding Iteration Comparison

| <b>Eb/No (dB)</b> | <b>SPA</b> | <b>MSA</b> |
|-------------------|------------|------------|
| <b>1</b>          | 18         | 14         |
| <b>3</b>          | 14         | 11         |
| <b>5</b>          | 10         | 8          |
| <b>7</b>          | 7          | 6          |
| <b>9</b>          | 5          | 4          |

The number of decoding iterations decreased steadily as the channel quality improved for both algorithms. At low signal-to-noise ratios, more iterations were required to correct the larger number of transmission errors introduced by the noisy communication channel. Conversely, at higher  $E_b/N_0$  values, fewer decoding iterations were sufficient because the received information contained fewer corrupted bits.

Throughout the simulation, MSA consistently required fewer decoding iterations than SPA. At 1 dB, SPA required 18 iterations compared with 14 for MSA. Similarly, at 3 dB and 5 dB, SPA required 14 and 10 iterations, whereas MSA converged after 11 and 8 iterations, respectively. At the highest simulated signal-to-noise ratio of 9 dB, SPA required 5 iterations, while MSA converged after only 4 iterations.

The average iteration count was 10.8 for SPA and 8.6 for MSA. This reduction in decoding iterations explains the lower computational energy observed for the Min-Sum Algorithm. Since decoding energy is directly related to the amount of computational processing performed during iterative decoding, fewer iterations translate directly into lower energy consumption.

#### 4. Conclusion

This study presented a comparative evaluation of the Sum-Product Algorithm (SPA) and the Min-Sum Algorithm (MSA) for LDPC decoding over an AWGN channel, with emphasis on the trade-off between communication reliability and estimated decoding energy. Both decoders were evaluated under identical MATLAB R2019b simulation conditions using BPSK modulation, a rate-1/2 LDPC code, and  $E_b/N_0$  values from 1 to 9 dB. BER, average decoding iterations, and estimated Decoding Energy per Bit (DEB) were used to evaluate the reliability and computational-efficiency characteristics of the two algorithms.

The results showed that SPA consistently achieved lower BER than MSA across the investigated  $E_b/N_0$  range. SPA produced an average BER of 0.00528, compared with 0.00956 for MSA, demonstrating the reliability advantage of the full probabilistic message-passing approach. Although the BER difference between the algorithms became smaller in absolute terms as  $E_b/N_0$  increased, SPA retained the lower BER at every simulated operating point. The results therefore indicate that the Min-Sum approximation incurs a measurable reliability penalty under the conditions investigated.

In contrast, MSA required fewer decoding iterations throughout the simulation. The average iteration count was 8.6 for MSA compared with 10.8 for SPA. Under the adopted iteration-based energy model, DEB was calculated using 0.0500 nJ/bit/iteration, resulting in average estimated DEB values of 0.43 nJ/bit for MSA and 0.54 nJ/bit for SPA. Thus, MSA achieved approximately 20.4% lower average estimated DEB than SPA. This energy advantage follows directly from the lower number of decoding iterations required by MSA under the adopted common coefficient; the present simulation does not independently establish that an individual MSA iteration consumes less energy than an individual SPA iteration.

The findings demonstrate a clear reliability–energy trade-off in iterative LDPC decoding. SPA is preferable when the primary design objective is maximum decoding reliability, whereas MSA provides a lower-iteration and lower-estimated-energy alternative when a moderate degradation in BER can be tolerated. This trade-off is particularly

relevant to WSN applications, where decoding energy can contribute materially to the limited energy budget of sensor nodes.

## 5. Recommendations

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

1. The Min-Sum Algorithm should be considered for energy-constrained Wireless Sensor Networks, where reduced computational complexity and lower decoding energy consumption are critical design requirements.
2. The Sum-Product Algorithm should be adopted in applications requiring very high decoding accuracy, particularly in communication systems where reliability is more important than computational cost.
3. Future research should investigate optimized variants of the Min-Sum Algorithm, such as the Normalized Min-Sum (NMS) and Offset Min-Sum (OMS) algorithms, to further improve BER performance while maintaining low decoding complexity.
4. Future investigations should extend the comparison to more realistic wireless channel models, such as Rayleigh and Rician fading channels, to evaluate the robustness of SPA and MSA under practical propagation conditions.
5. Hardware implementation using FPGA or ASIC platforms is recommended to validate the computational efficiency and energy savings observed in simulation and to assess the feasibility of deploying these decoding algorithms in real-time communication systems.

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