

# **Polar Codes:**

**A New Way Of Achieving Shannon Capacity**

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**Prepared by Lab Group 6 - Group 1**

# Honor Code

We declare that

- The work that we are presenting is our own work.
- We have not copied the work (the code, the results, etc.) that someone else has done.
- Concepts, understanding and insights we will be describing are our own.
- We make this pledge truthfully. We know that violation of this solemn pledge can carry grave consequences.

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# Introduction

Polar Codes were discovered by Erdal Arikan in 2008. They have become the most favourable codes for Forward Error Correction since then. They are notable for being first in their types with provable capacity-achieving property. Polar codes have especially found their application in the 5G wireless communication.



# **An Analogy to Understand Polar Codes**

# Why Polar Codes?

Polar codes propose a new approach to achieve the Shannon capacity. Instead of encoding data bits like traditional methods, polar codes polarize the channel into two extreme channels: highly reliable and less reliable. They then utilize the highly reliable channels to transfer the data bits, unlike different pre-existing coding techniques that focus on encoding the data bits. Thus, Polar Codes provide ease by working directly over channels rather than the data bits.



# **Analyzing the Differences Between Polar Codes and LDPC Codes**

# Factors:

## 1. **Shannon capacity:**

- LDPC: Operates near the Shannon limit for high reliability.
- Polar: Can match Shannon capacity in ideal scenarios.

## 2. **BER:**

- Polar: Low BER for short messages.
- LDPC: Superior BER for long messages.

## 3. **Throughput:**

- LDPC: High throughput, ideal for large data volumes.
- Polar: Potential throughput limitations for extensive data streams.

## 4. **Latency:**

- Polar: Lower latency, suitable for real-time applications.
- LDPC: Slightly higher latency, especially for time-sensitive tasks.

# **Polar Transformation**

Let  $X$  be a Bernoulli Random Variable  $X \sim p_x$  on  $x = \{0, 1\}$

Let  $X_1, X_2, \dots, X_n$  be iid  $\sim X$

For  $N = 2^n, n \geq 1$

$U \rightarrow$  a new transformed Random vector  $U^N = X^N F^{\otimes n}, F = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$

Where  $U^N = (U_1 U_2 \dots U_N)$   
 $X^N = (X_1 X_2 \dots X_N)$

For example,

Let's consider  $n = 1 \implies N = 2^1 = 2$

So,  $U^2 = (U_1, U_2)$  and  $X^2 = (X_1, X_2)$

$$(U_1, U_2) = (X_1, X_2) \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}^{\otimes 1}$$

$$(U_1, U_2) = (X_1 + X_2, X_2)$$

For  $n = 2$ ,  $N = 2^2 = 4$

$$\begin{aligned}
(U_1 \ U_2 \ U_3 \ U_4) &= (X_1 X_2 X_3 X_4) F^{\otimes 2} \\
&= (X_1 X_2 X_3 X_4) F^{\otimes 1} \otimes F \\
&= (X_1 X_2 X_3 X_4) \begin{bmatrix} F^{\otimes 1} & [0]_{2 \times 2} \\ F^{\otimes 1} & F^{\otimes 1} \end{bmatrix} \\
&= (X_1 X_2 X_3 X_4) \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}
\end{aligned}$$

$$(U_1 \ U_2 \ U_3 \ U_4) = (X_1 + X_2 + X_3 + X_4 \ X_2 + X_4 \ X_3 + X_4 \ X_4)$$

For a general  $n$ , we define kronecker product as

$$F^{\otimes n} = F^{\otimes(n-1)} \otimes F$$

$$F^{\otimes n} = \begin{bmatrix} F^{\otimes(n-1)} & O \\ F^{\otimes(n-1)} & F^{\otimes(n-1)} \end{bmatrix}, \text{ where } O = [0]_{n \times n}$$

# **Theorem of** **Polarization**

# **How Polar Codes work?**



For Symmetric Channels, the capacity is given by:

$$I(W) \triangleq I(X; Y)$$

with  $X \sim \text{unif}\{0, 1\}$ .

Using base 2 algorithms:

$$0 \leq I(W) \leq 1$$

Perfect Channel:  $I(W) = 1$ , Useless Channel:  $I(W) = 0$

**Erikan's** polar transformation converts ordinary channels to such extreme channels by first combining them and then splitting them:

$$X_1 = U_1 \oplus U_2$$

$$X_2 = U_2$$

If  $U_1$  and  $U_2$  are distributed uniformly over  $\{0, 1\}$ , then  $X_1$  and  $X_2$  are also independent and uniformly distributed over  $\{0, 1\}$ .

$$I(X_1X_2; Y_1Y_2) = I(X_1; Y_1) + I(X_2; Y_2) = 2I(W)$$

$$I(U_1U_2; Y_1Y_2) = I(X_1X_2; Y_1Y_2) = 2I(W)$$

$$2I(W) = I(U_1U_2; Y_1Y_2)$$

$$2I(W) = I(U_1; Y_1Y_2) + I(U_2; Y_1Y_2|U_1) \quad (\text{Using the chain rule})$$

$$2I(W) = I(U_1; Y_1Y_2) + I(U_2; Y_1Y_2U_1)$$

$$2I(W) = I(W^-) + I(W^+)$$

So,

$$I(W^+) = I(U_2; Y_1Y_2|U_1) \geq I(U_2; Y_2) = I(X_2; Y_2) = I(W)$$

$$2I(W) = I(W^-) + I(W^+)$$

Therefore,

$$I(W^-) \leq I(W) \leq I(W^+)$$

Let us take a look at a binary erasure channel defined as BEC( $e$ ).  
Consider  $W^-$

$$U_1 \rightarrow (Y_1, Y_2)$$

Input is  $U_1$  and output is given as :  $(Y_1, Y_2)$

$$(Y_1, Y_2) = (U_1 \oplus U_2, U_2) \text{ with } p = (1 - e)^2$$

$$(Y_1, Y_2) = (?, U_2) \text{ with } p = (1 - e)e$$

$$(Y_1, Y_2) = (U_1 \oplus U_2, ?) \text{ with } p = (1 - e)e$$

$$(Y_1, Y_2) = (?, ?) \text{ with } p = e^2$$

Erasure probability =  $1 - (1 - e)^2 = 2e - e^2$ .

Consider  $W^+$

$$U_2 \rightarrow (Y_1, Y_2, U_1)$$

Input is  $U_2$  and output is given as :  $(Y_1, Y_2, U_1)$

$$(Y_1, Y_2, U_1) = (U_1 \oplus U_2, U_2, U_1) \text{ with } p = (1 - e)^2$$

$$(Y_1, Y_2, U_1) = (?, U_2, U_1) \text{ with } p = (1 - e)e$$

$$(Y_1, Y_2, U_1) = (U_1 \oplus U_2, ?, U_1) \text{ with } p = (1 - e)e$$

$$(Y_1, Y_2, U_1) = (?, ?, U_1) \text{ with } p = e^2$$

Erasure probability =  $e^2$ .

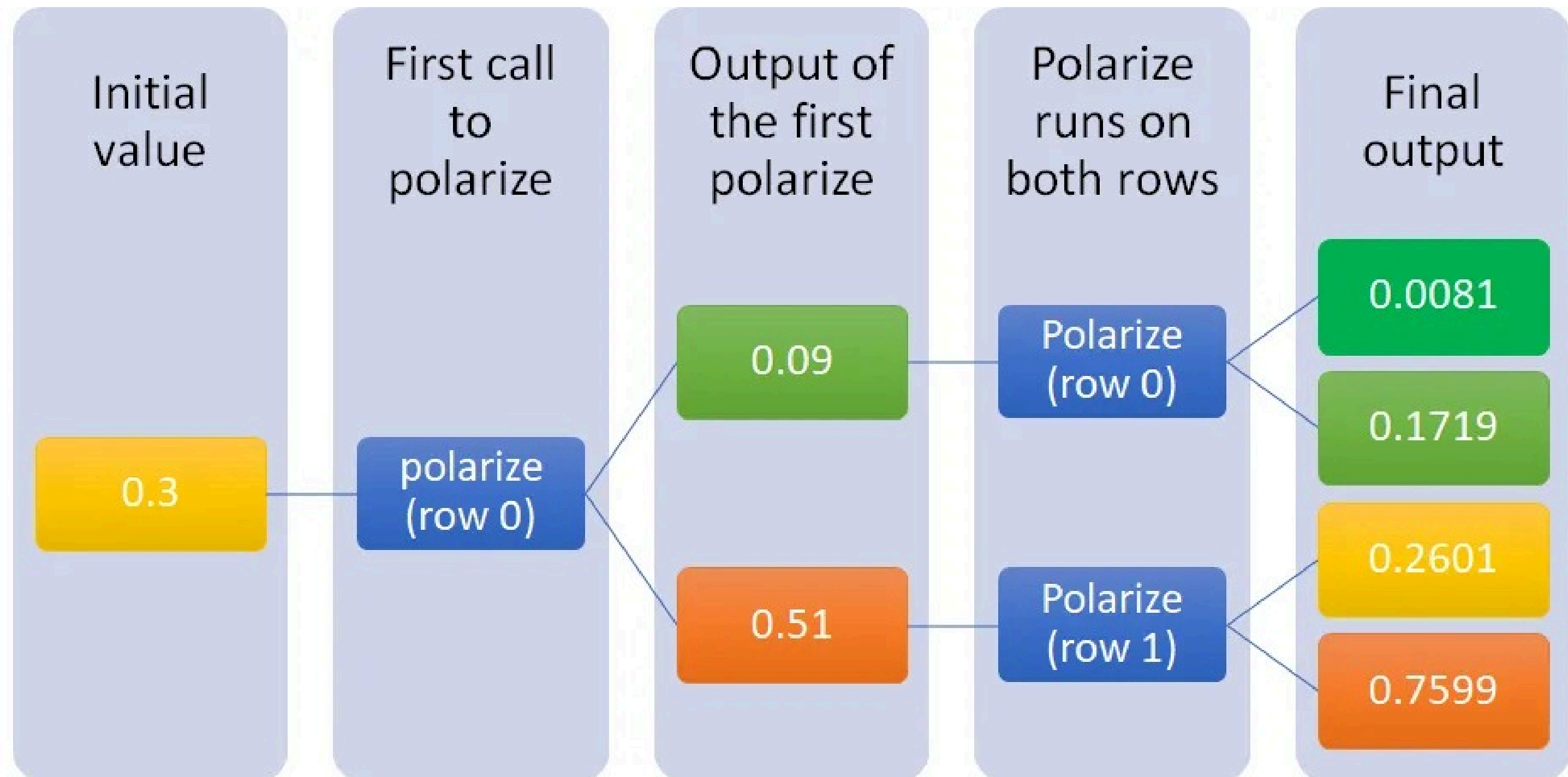
The channel is split into  $W^+$  and  $W^-$ .

The channel  $W^+$  has an erasure probability( $e^+$ ) of  $e^2$ . The channel  $W^-$  has an erasure probability( $e^-$ ) of  $2e - e^2$ .

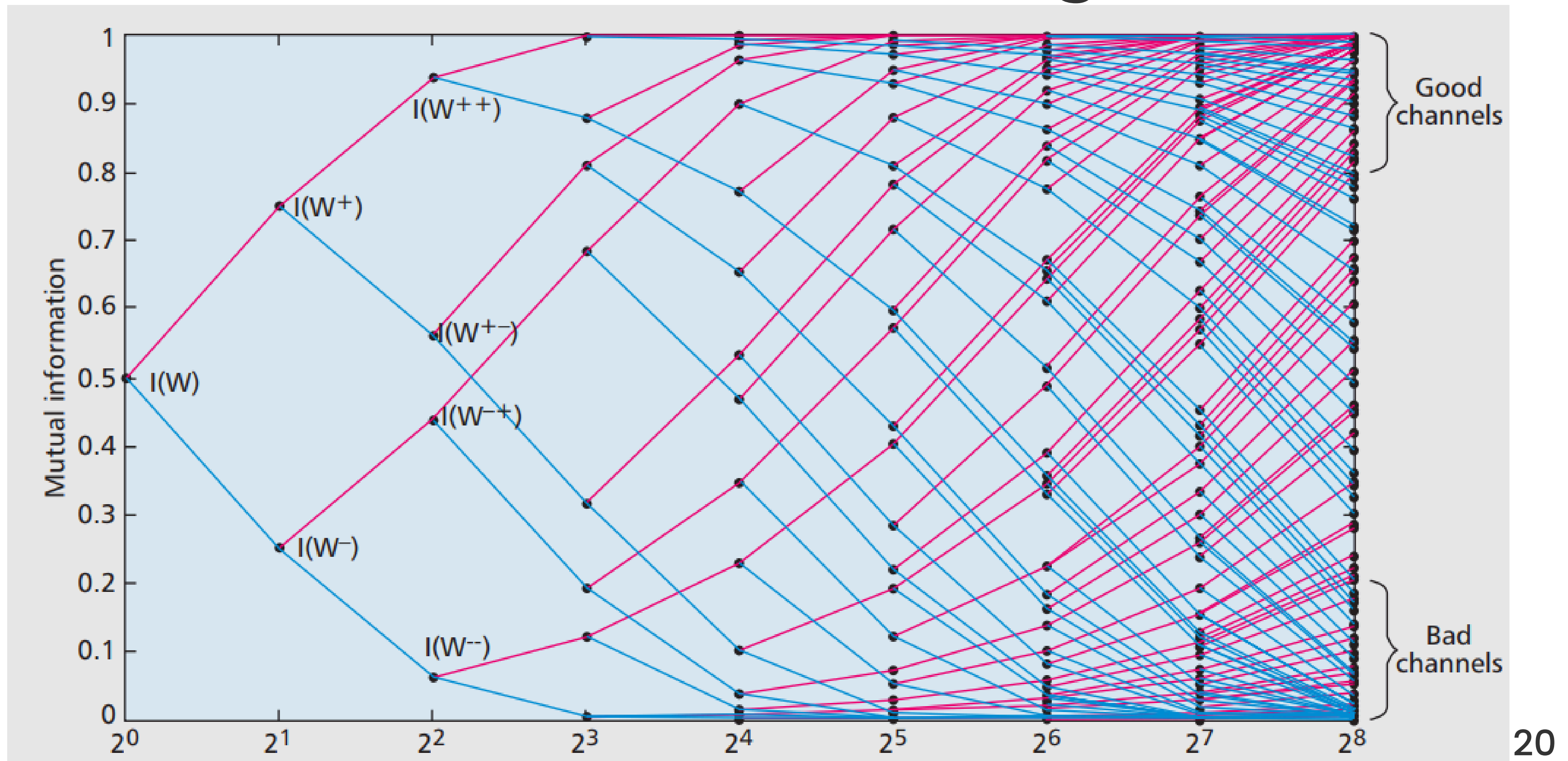
Now for Binary Symmetric channel with error probability  $p$  the same equation will hold, only the erasure probability will be replaced by the error probability. Further notice that value of  $e^+ + e^- = 2e$ .

This holds from

$$2I(W) = I(W^-) + I(W^+)$$

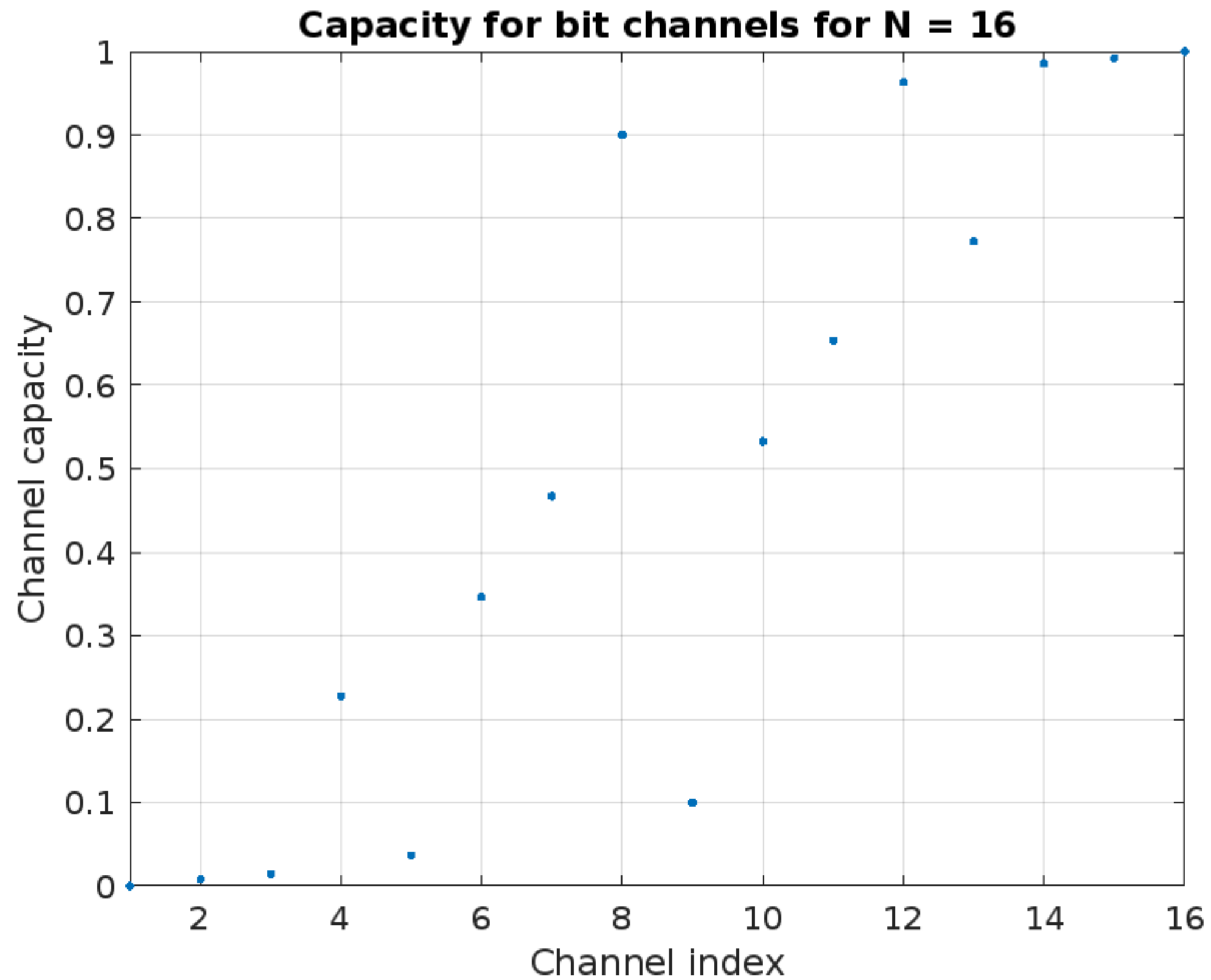


# Polarization Martingale

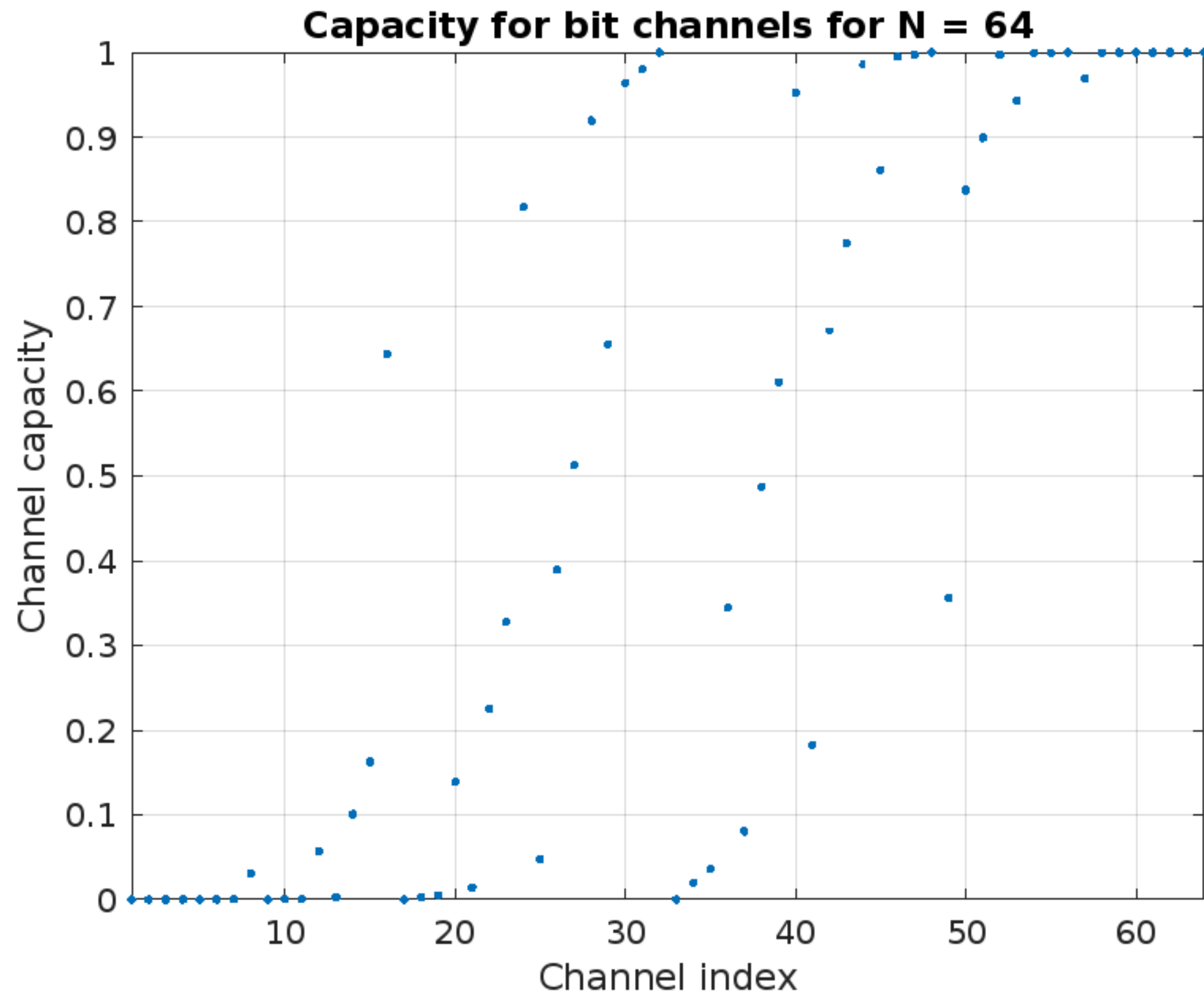




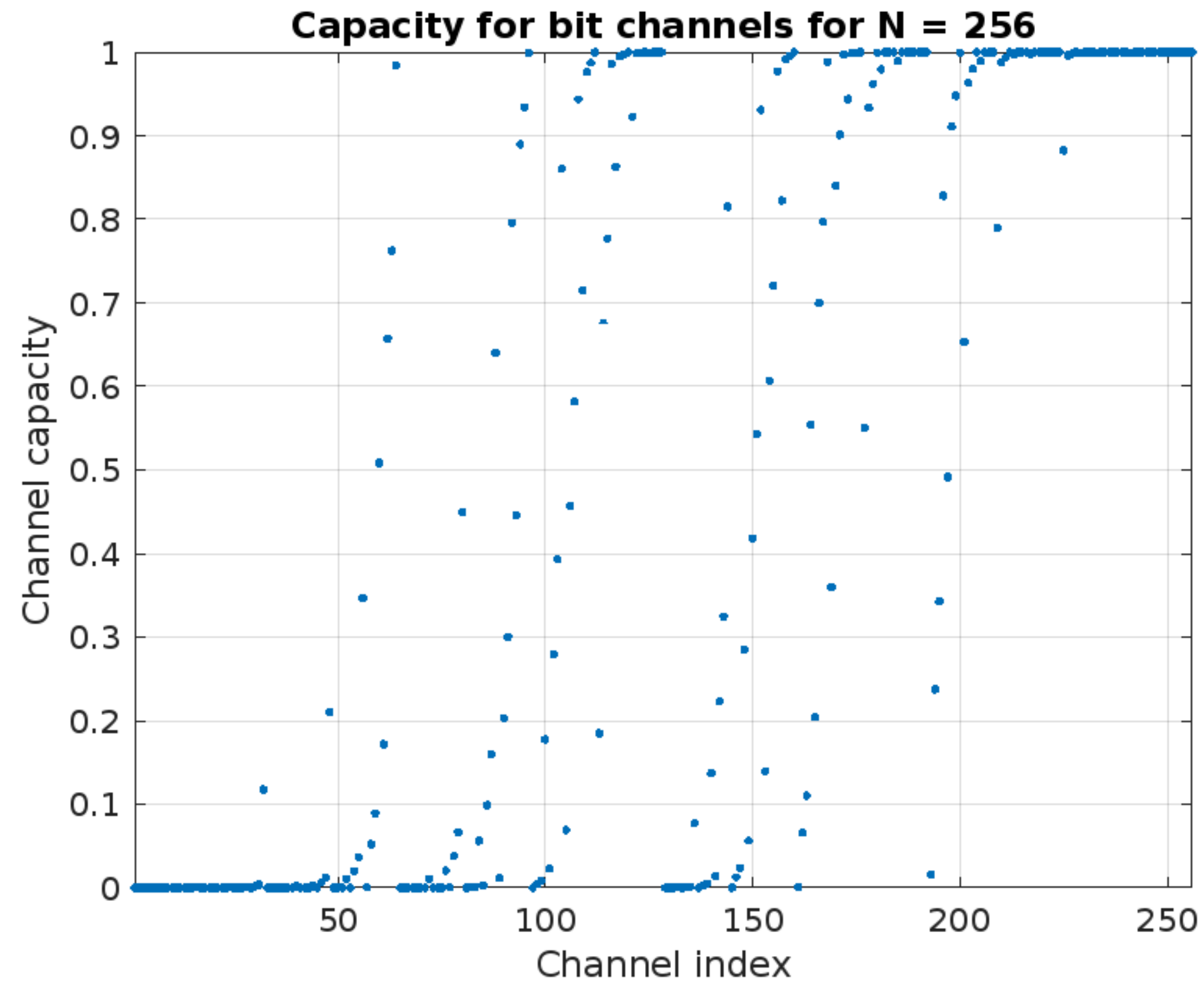
# Polarization of BEC(1/2) for N=16



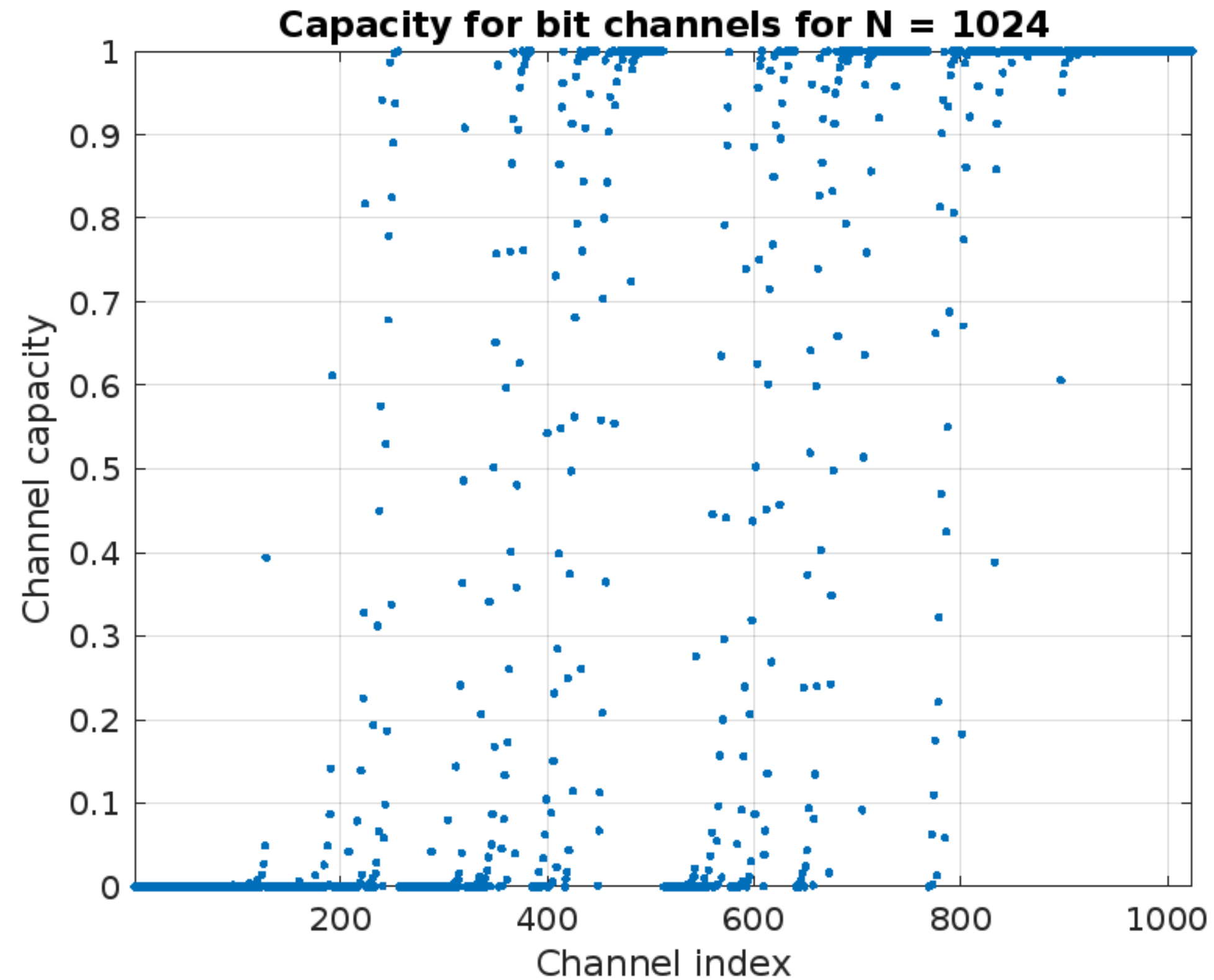
# Polarization of BEC Rate (1/2) N=64

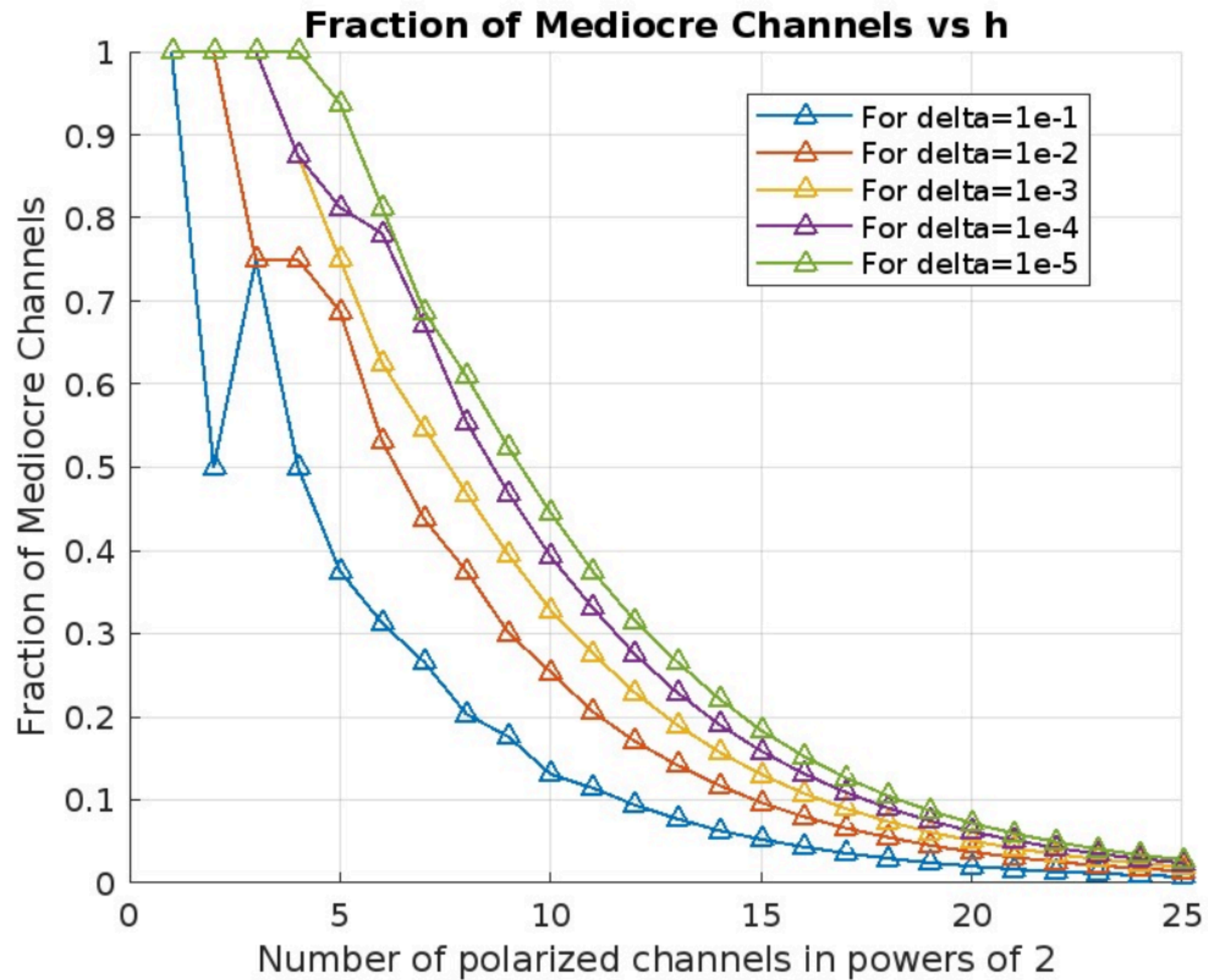


# Polarization of BEC Rate (1/2) N=256



# Polarization of BEC(1/2) for N=1024





# Observations :

- In polar codes, as the value of  $N$  (representing the number of channels) increases, the number of channels approaching capacity extremes (0 or 1) also increases.
- We observe a greater quantity of extreme channels compared to mediocre ones.
- Polar codes strategically allocate frozen bits to channels with poor performance (the "worst" channels) and reserve efficient channels for transmitting message bits.
- This allocation minimizes error probability by leveraging channel characteristics.
- As  $N$  tends towards infinity, the error probability diminishes significantly, converging towards Shannon capacity.
- This demonstrates the remarkable efficiency and effectiveness of polar codes in maximizing transmission reliability.

# Encoding Algorithm



# Reliability Sequence:

- It is a sequence which gives a sorted order of channels starting from worst channels to the best channels according to the efficiency of the output.
- For N=16 the reliability sequence is:  
1 2 3 5 9 4 6 10 7 11 13 8 12 14 15 16
- The reliability sequence is derived using the **Bhattacharya Parameter**, which is defined as below:

$$Z(W) \triangleq \sum_{y \in Y} \sqrt{W(y|0)W(y|1)}, \text{ where } Z(W) \text{ takes values in } [0, 1] \text{ and } W \text{ is a B-DMC (Binary Discrete Memoryless Channel).}$$

Suppose we have a message  $m$  having  $K$  bits. We need to generate a codeword  $C$  having  $N$  ( $N=2^3$ ) bits.

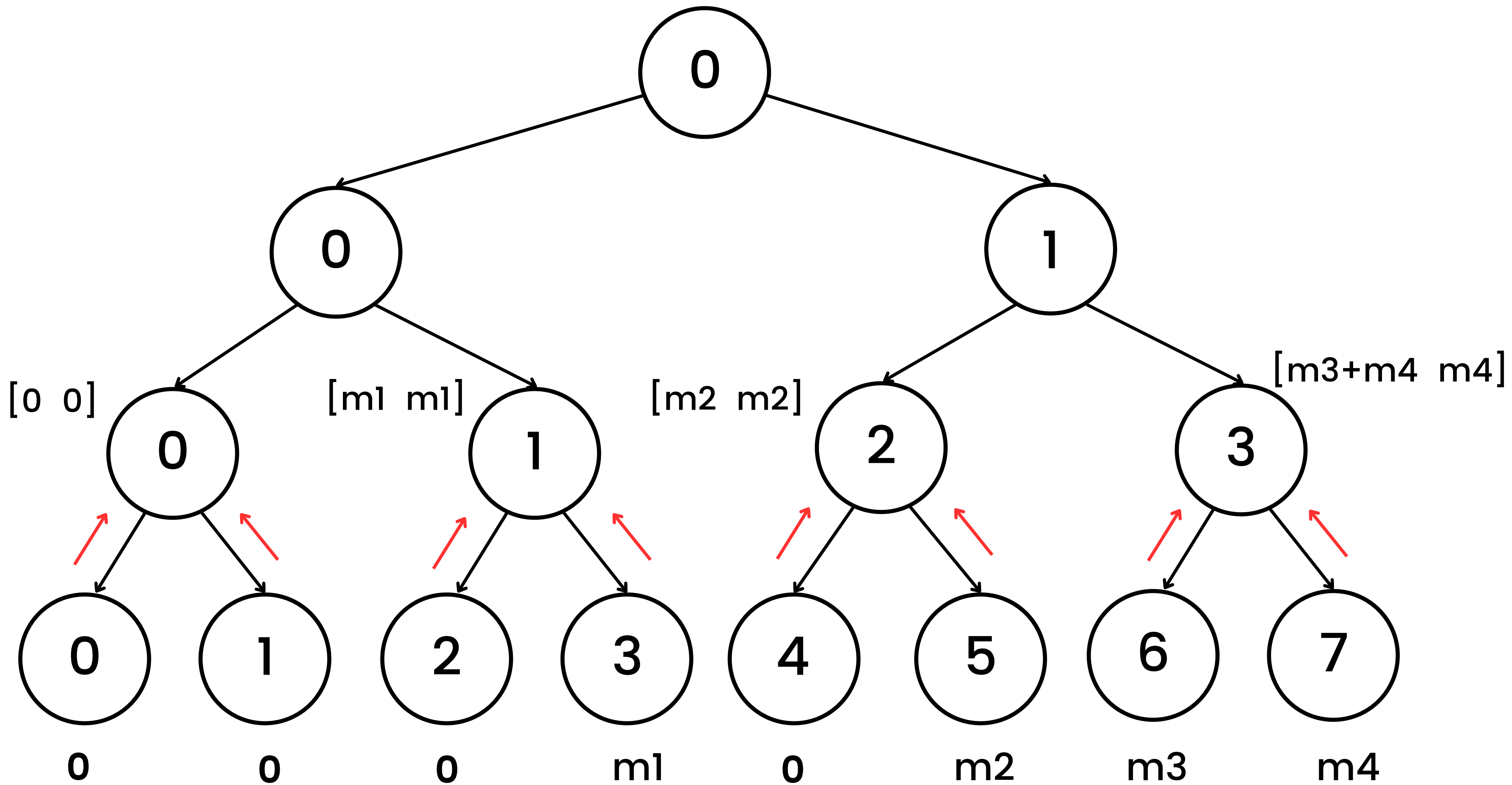
## Algorithm:

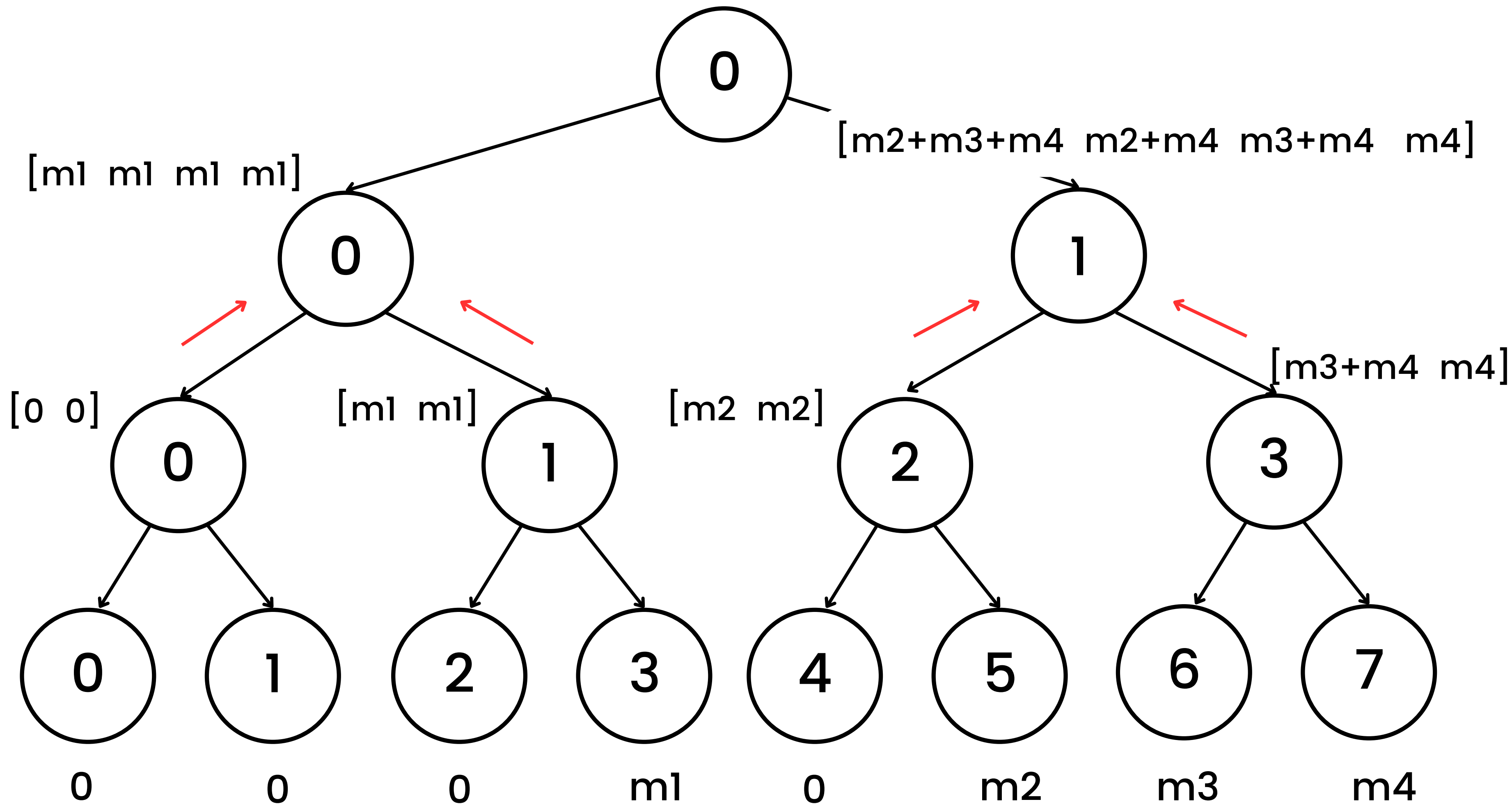
1. Find first  $N-K$  worst channels for  $N$  based on the reliability sequence.
2. For all the  $N-K$  positioned indexes in the vector  $u$  we set the bits to zero. These positions are also known as **Frozen Positions**.
3. Set the remaining  $K$  bits of vector  $u$  as the message bits.
4. Now, to generate the final codeword or the encoded message we need to multiply vector  $u$  with the Generator Matrix  $G_n$  based on the polar transform defined earlier.

$$\text{Codeword } C = u \cdot G_n$$

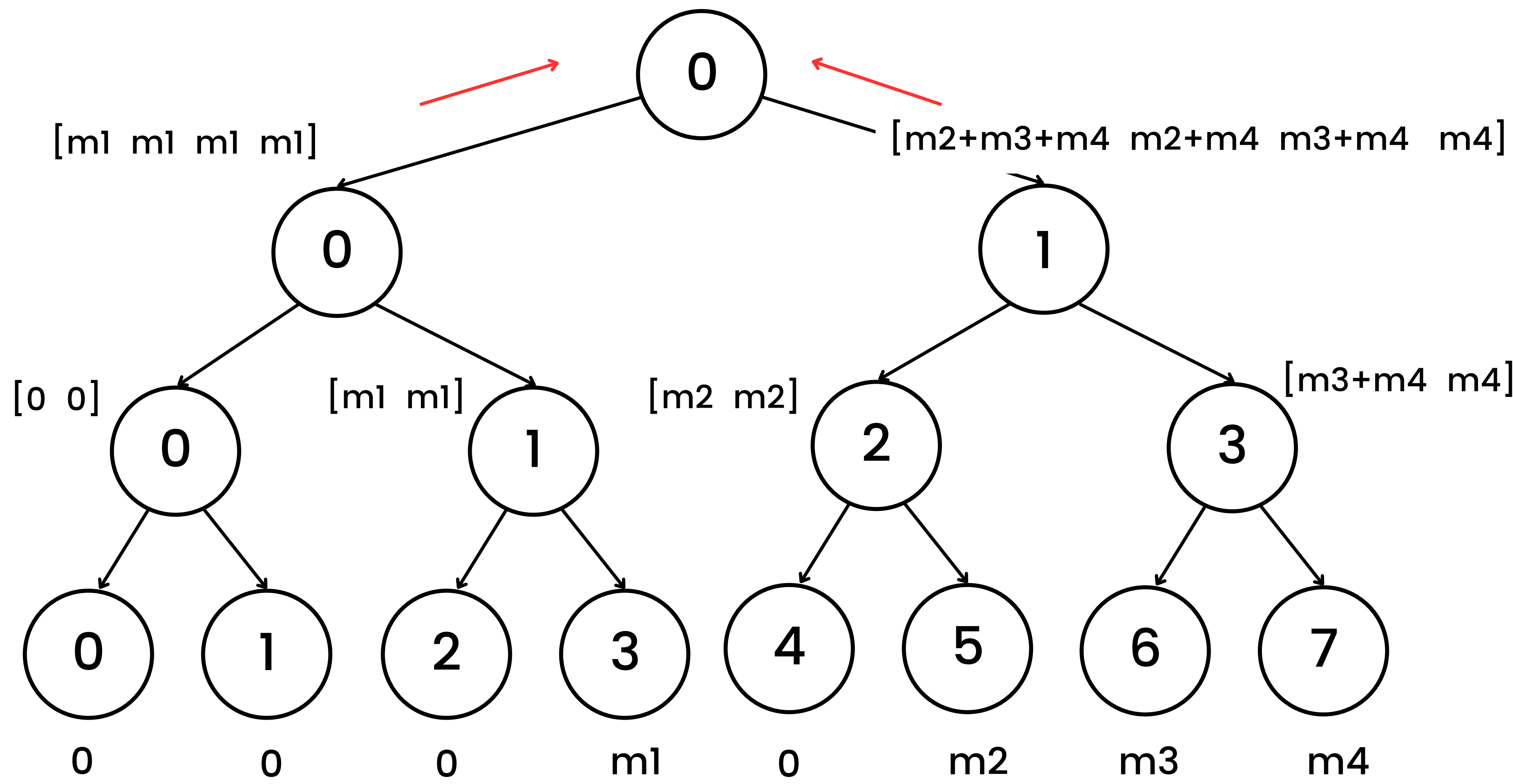
## Example:

- Message  $m$ : 4 Bits ( $K=4$ )
- Codeword  $C$ : 8 Bits ( $N=2^3$ )
- Reliability Sequence: 1 2 3 5 4 6 7 8

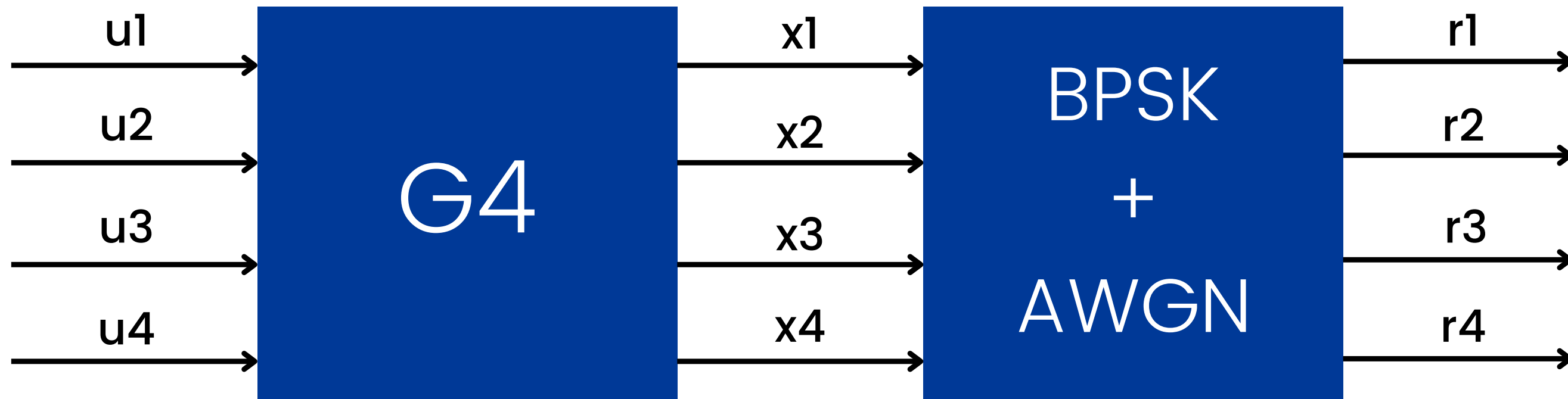




$C = [m1+m2+m3+m4 \quad m1+m2+m4 \quad m1+m3+m4 \quad m1+m4 \quad m2+m3+m4 \quad m2+m4 \quad m3+m4 \quad m4]$



# **AWGN and BPSK**



For a BPSK Channel the bit conversion scheme is

**1 is converted to -1**

**0 is converted to 1**

AWGN is added during transmission



# Decoding Algorithm

# Successive Cancellation Decoding

## Basic Building Block N=2 SC Decoder

There are two main functions we require for Successive Cancellation Decoder. They can also be described as two types of SISO decoders used in different parts of the SC decoding algorithm. They are as described below:

### **SISO Decode for $u_1$ (SPC)**

$$L(u_1) = f(r_1, r_2) = \text{sgn}(r_1)\text{sgn}(r_2)\min(|r_1|, |r_2|)$$

$$\hat{u}_1 = \begin{cases} 0, & \text{if } L(u_1) \geq 0. \\ 1, & \text{if } L(u_1) < 0. \end{cases}$$

### **Given $\hat{u}_1$ , Decode $u_2$ (Rep)**

$$\text{If } \hat{u}_1 = 0, \quad L(u_2) = r_2 + r_1 \quad (x = [u_2 \ u_2])$$

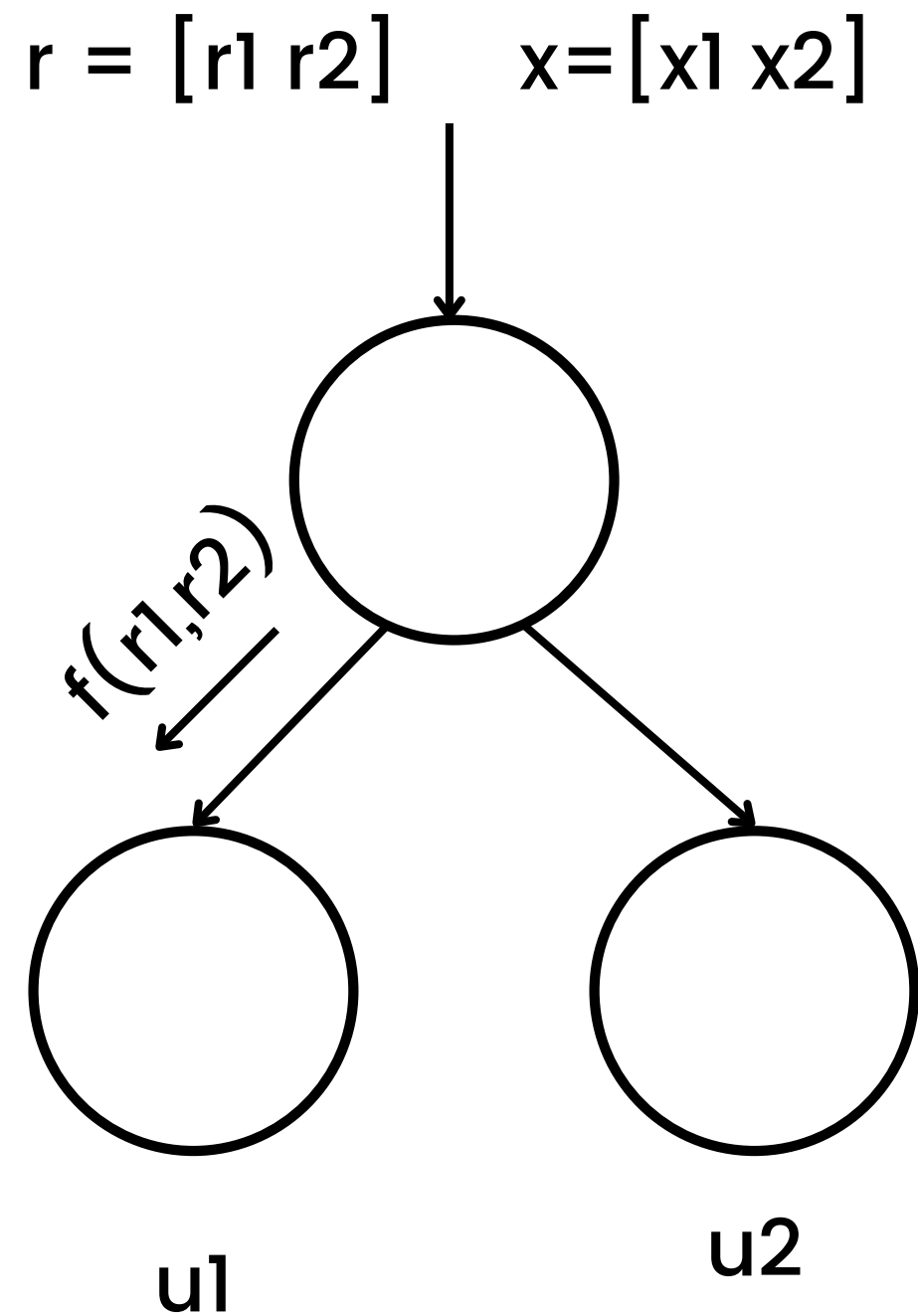
$$\text{If } \hat{u}_1 = 1, \quad L(u_2) = r_2 - r_1 \quad (x = [\bar{u}_2 \ u_2])$$

Both the cases together can be written as :

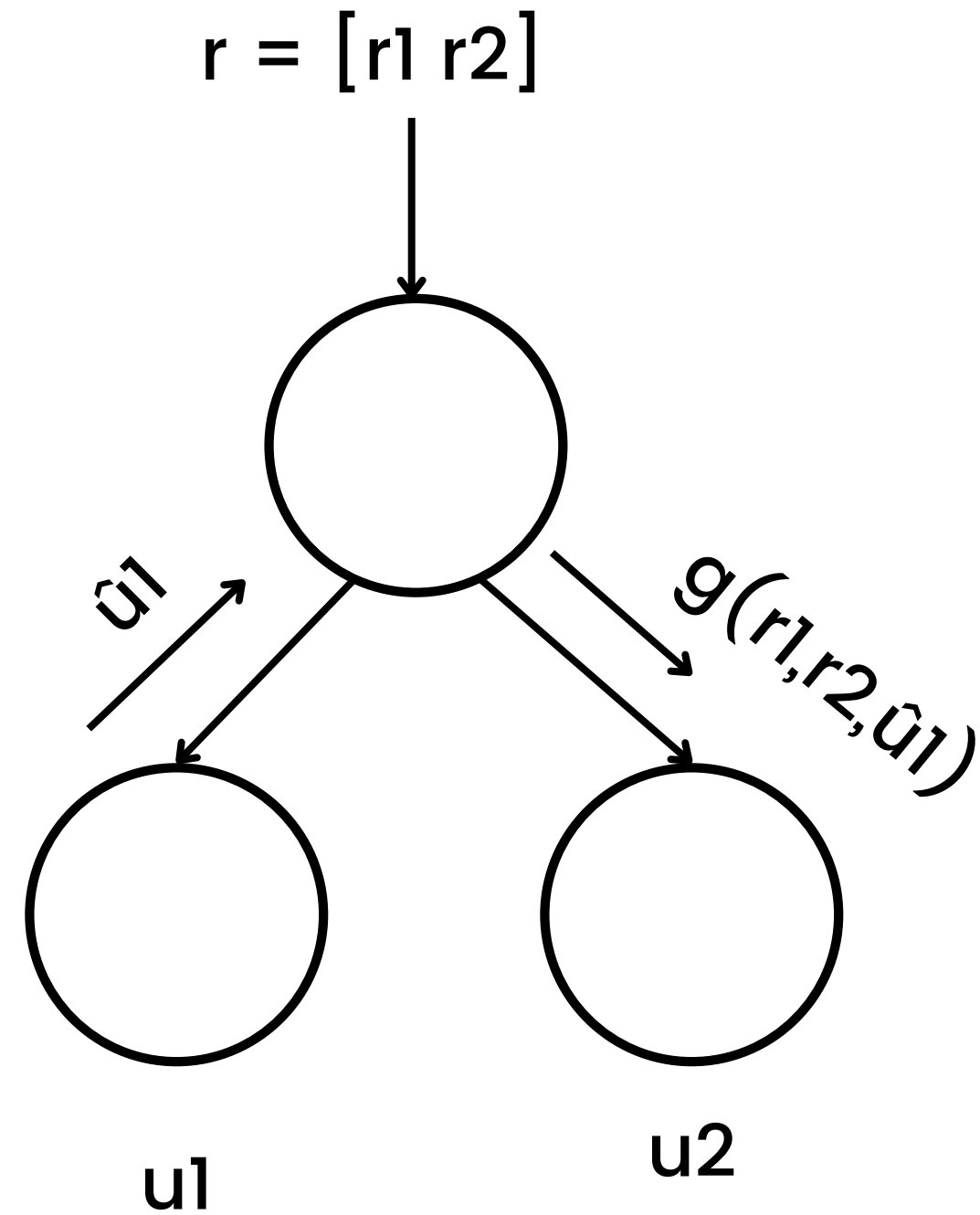
$$L(u_2) = g(r_1, r_2, \hat{u}_1) = r_2 + (1 - 2\hat{u}_1)r_1$$

# Successive Cancellation Decoding(N=2)

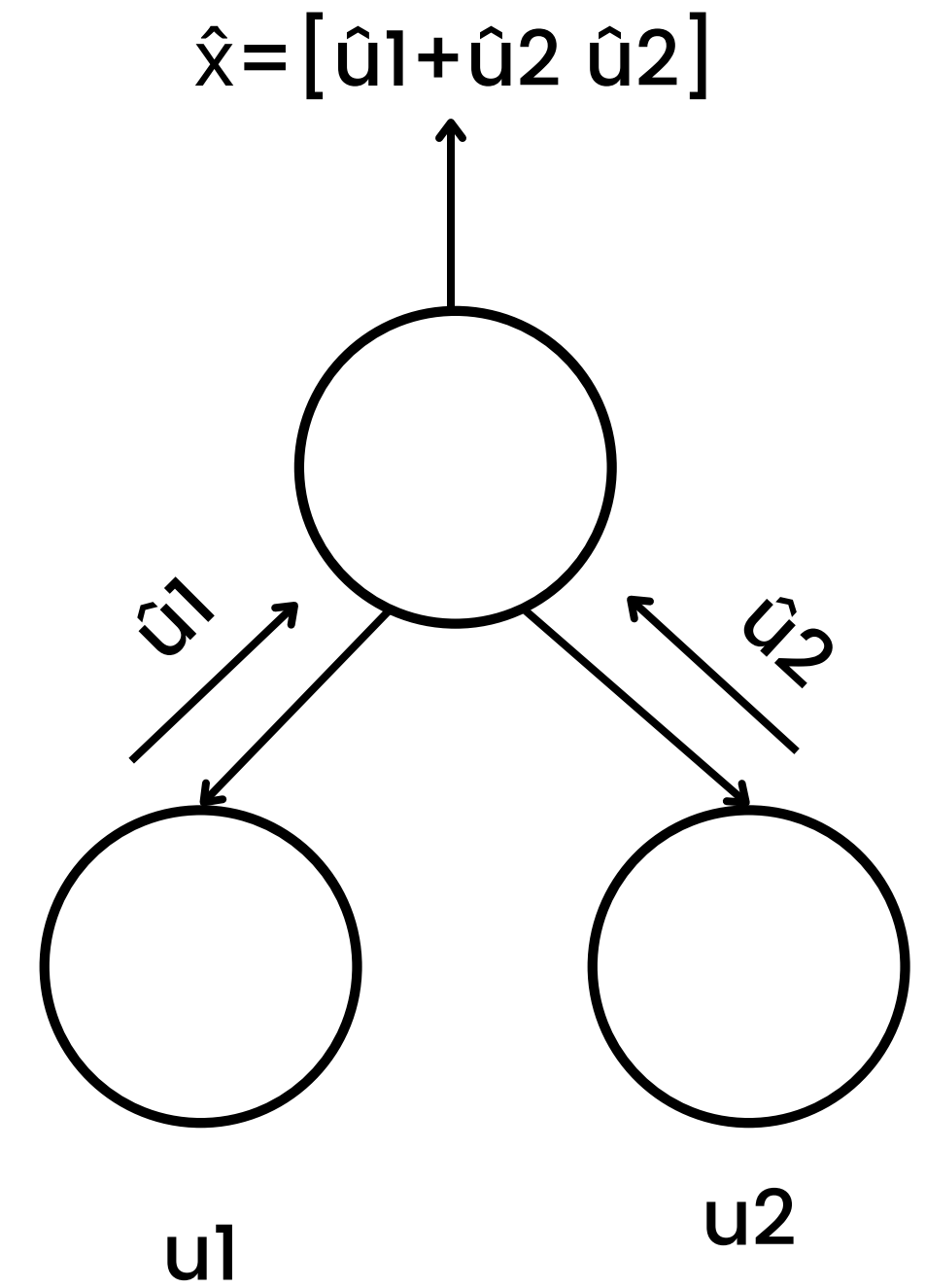
Step 1



Step 2



Step 3



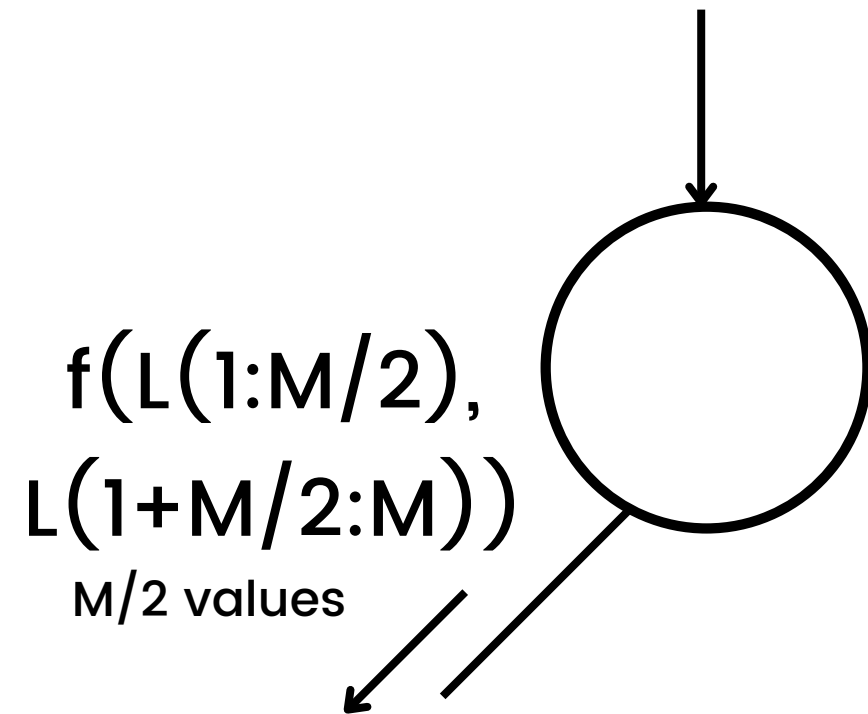
We repeat the above three steps till we traverse the whole tree (For  $N > 2$ )

# Successive Cancellation Decoding(for any N)

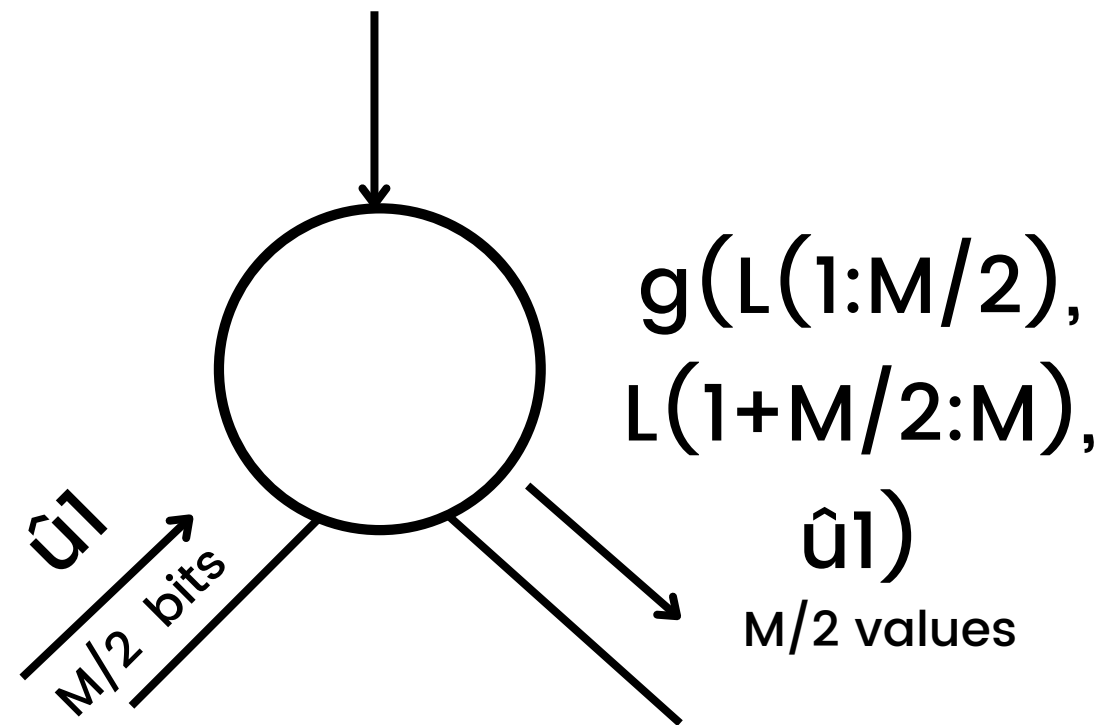
$$M = 2^m$$

Step L

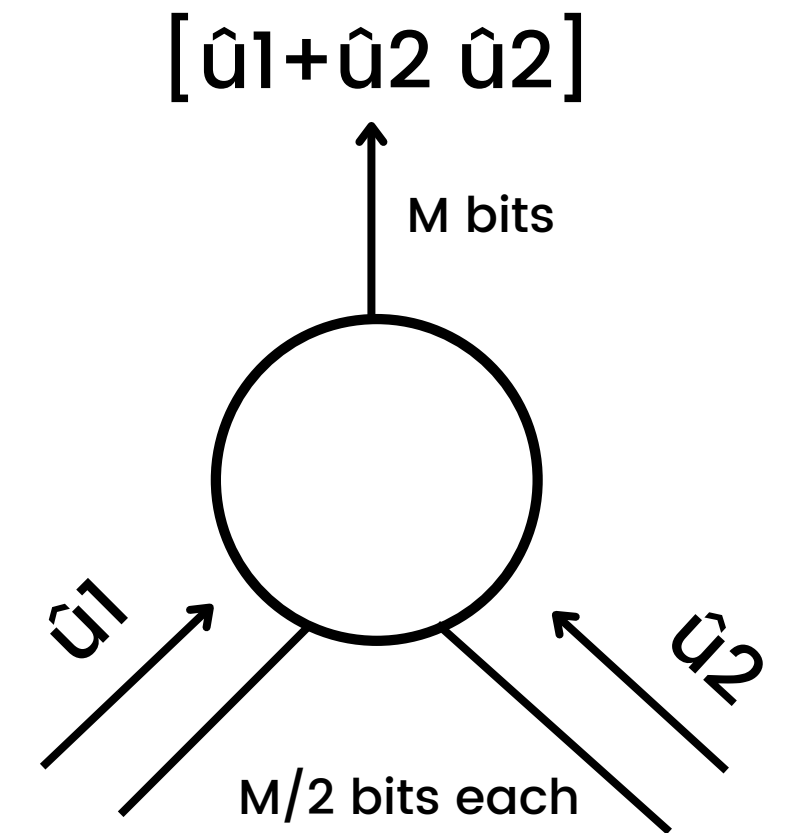
$$L = [L1 \ L2 \ \dots \ LM]$$



Step R



Step U

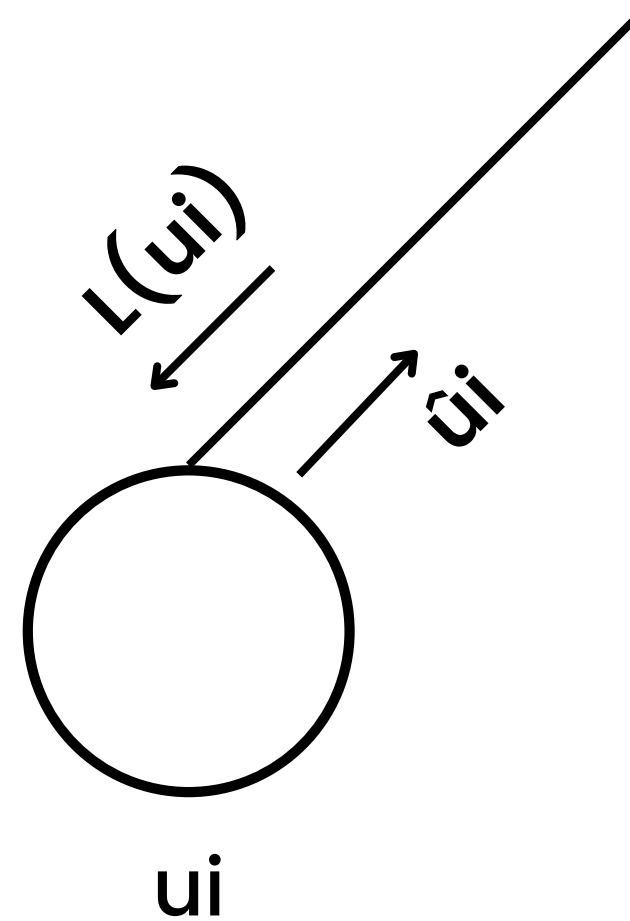


$$f(a(1:p), b(1:p)) = [f(a1, b1) f(a2, b2) \dots f(ap, bp)] \quad g(a(1:p), b(1:p), c) = [g(a1, b1, c1) g(a2, b2, c2) \dots g(ap, bp, cp)]$$

Here  $f$  and  $g$  functions are the same as defined earlier

We repeat the above three steps till we traverse the whole tree (For  $N > 2$ )

# Successive Cancellation Decoding(for any N)



If 'i' is a Frozen Position:  $\hat{u}_i=0$

If 'i' is a message Position:  $\hat{u}_i=0$ , if  $L(u_i) \geq 0$   
 $\hat{u}_i=1$ , if  $L(u_i) < 0$

We repeat the above step for all the leaf nodes till we traverse the whole tree (For  $N>2$ )

# Successive Cancellation Decoding

## Algorithm:

Start at the root.

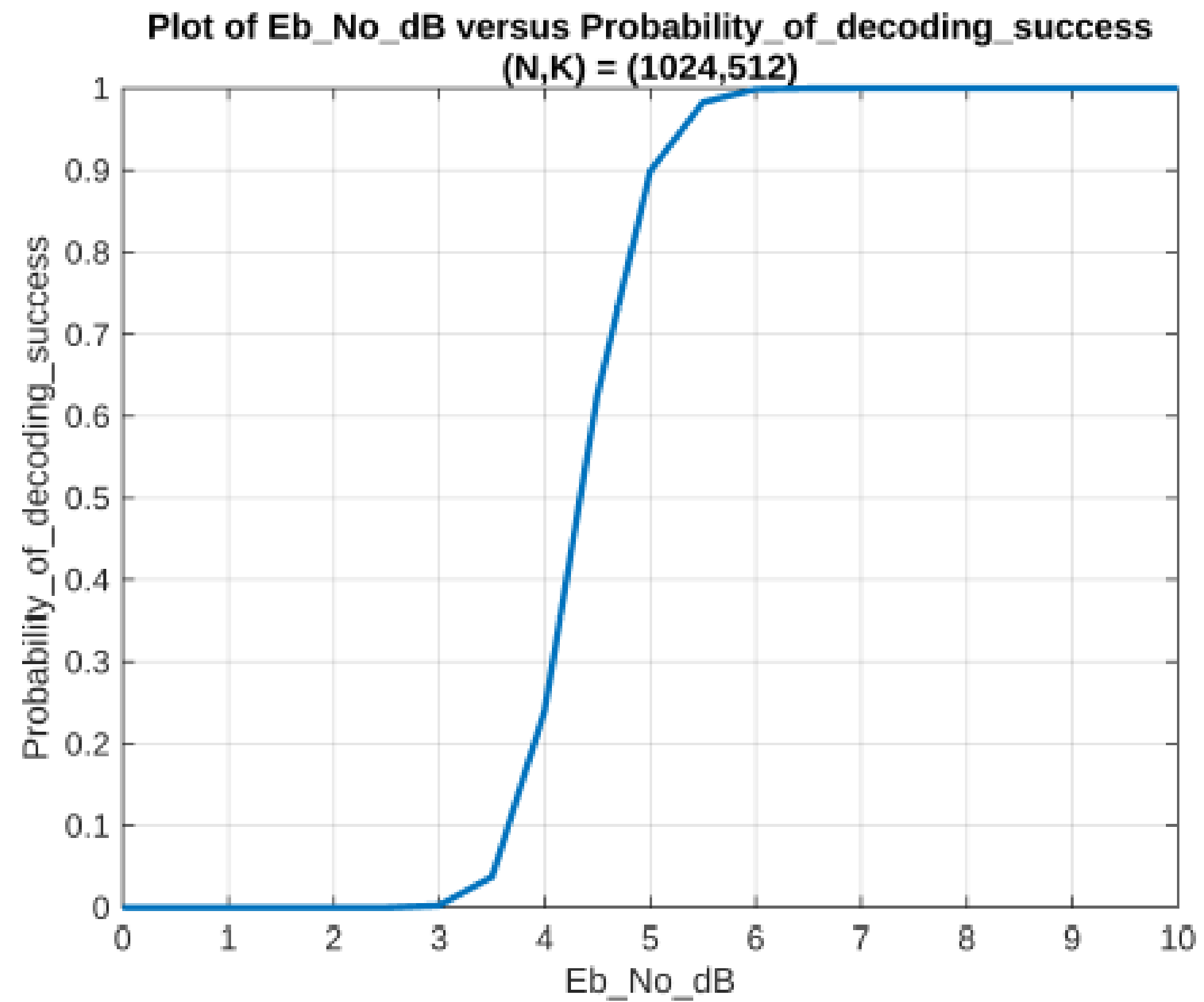
For intermediate nodes

1. Do step L and go to the left child.
2. Once the decision ( $\hat{u}_1$ ) is received from the left child, do step R and go to the right child
3. When decision is received from the right child ( $\hat{u}_2$ ), do step U and go to the parent.

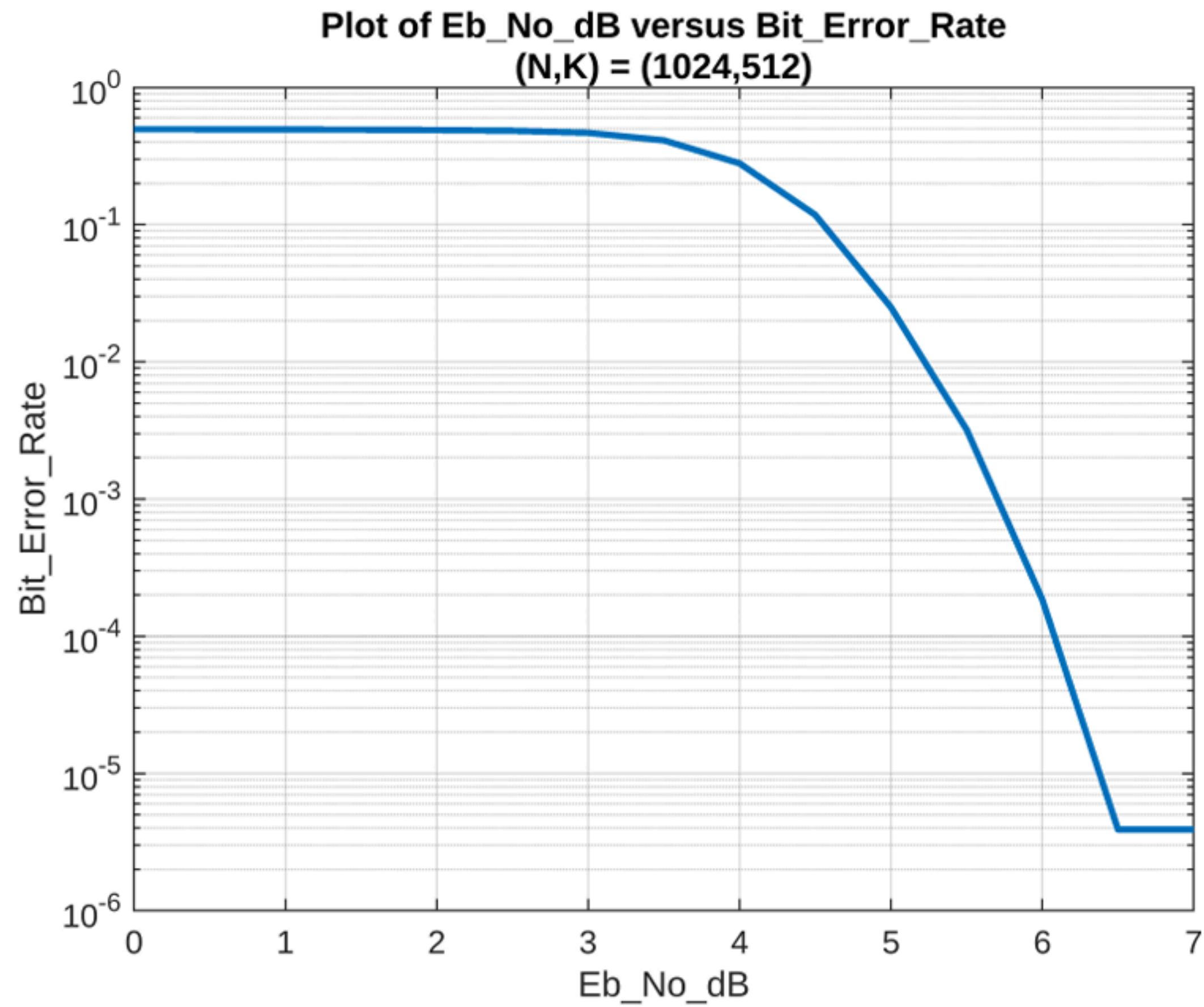
For Leaf nodes

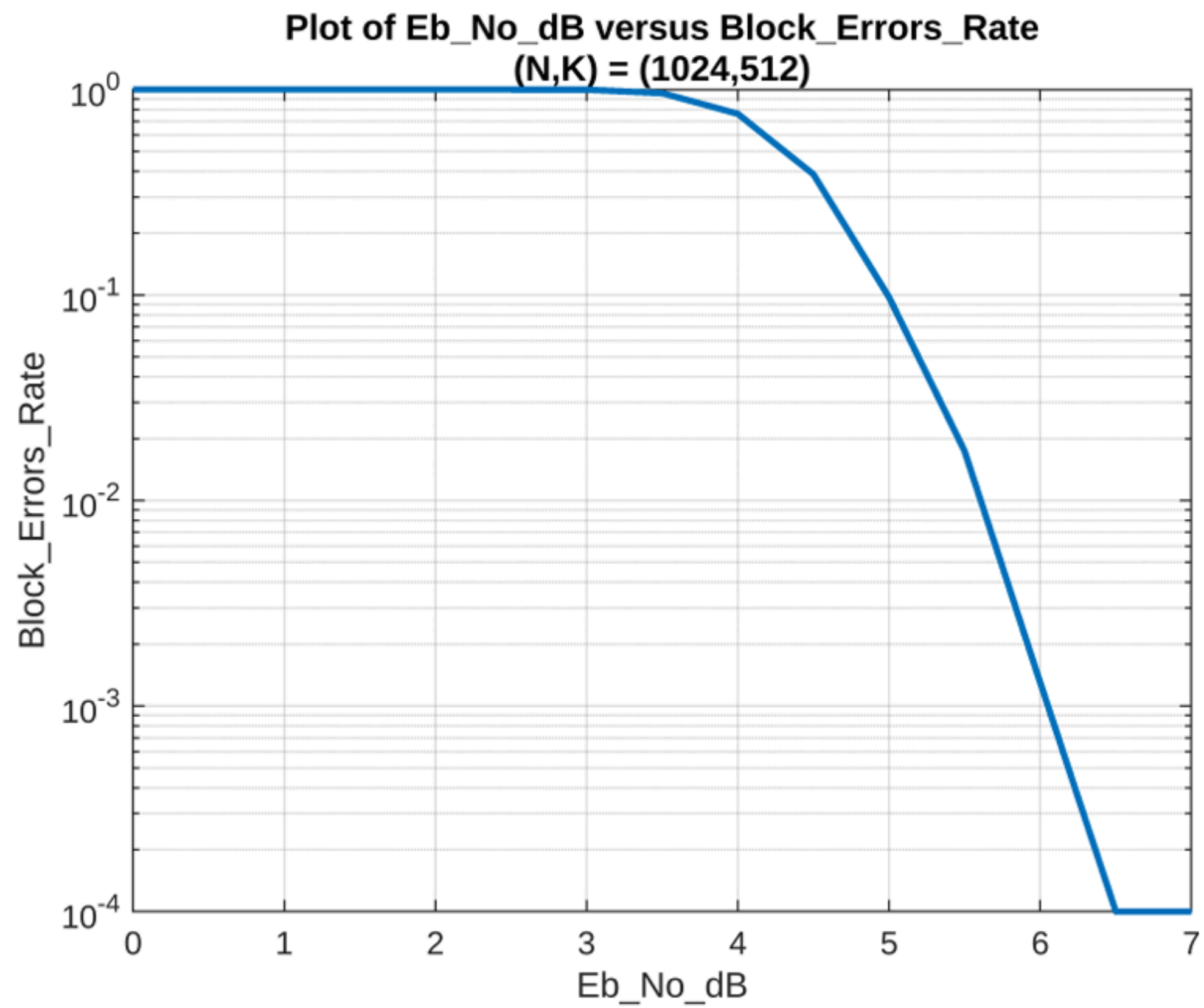
Leaf must make a decision and send it to the parent

# **Simulating Outputs**







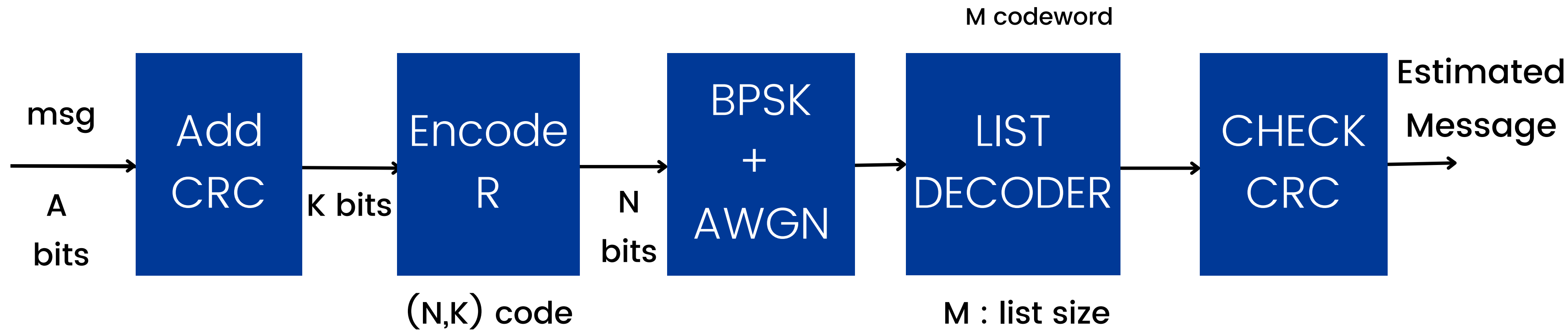


# Successive Cancellation Decoding : Disadvantages

- SC requires the decoding process to advance bit by bit. This results in high latency and low throughput when implemented in hardware.
- Polar codes decoded with SC only achieve the channel capacity when the code length tends toward infinity. For practical polar codes of moderate length, SC decoding cannot provide a reasonable error-correction performance.
- SCL Decoder is about 1dB better than SC decoder.

# Successive Cancellation List :

## Decoding Block Diagram



# Cyclic Redundancy Check (CRC)

- CRC is a method to detect error in digital networks. It is used to change accidental changes in data.
- In this method, we divide the message by a selected polynomial to get a remainder polynomial which we then append it to the end of message to form our new codeword which we then transmit.
- On the receiver side, after decoding, we divide decoded codeword by the selected CRC polynomial.
- If the remainder on division comes out to be zero then it is a valid codeword.

## Decision Metric

The decision metric can be described as follows:

If  $L(u_i) \geq 0$ , then:

- $\hat{u}_i = 0$  has  $DM = 0$ ,
- $\hat{u}_i = 1$  has  $DM = |L(u_i)|$ .

If  $L(u_i) < 0$ , then:

- $\hat{u}_i = 1$  has  $DM = 0$ ,
- $\hat{u}_i = 0$  has  $DM = |L(u_i)|$ .

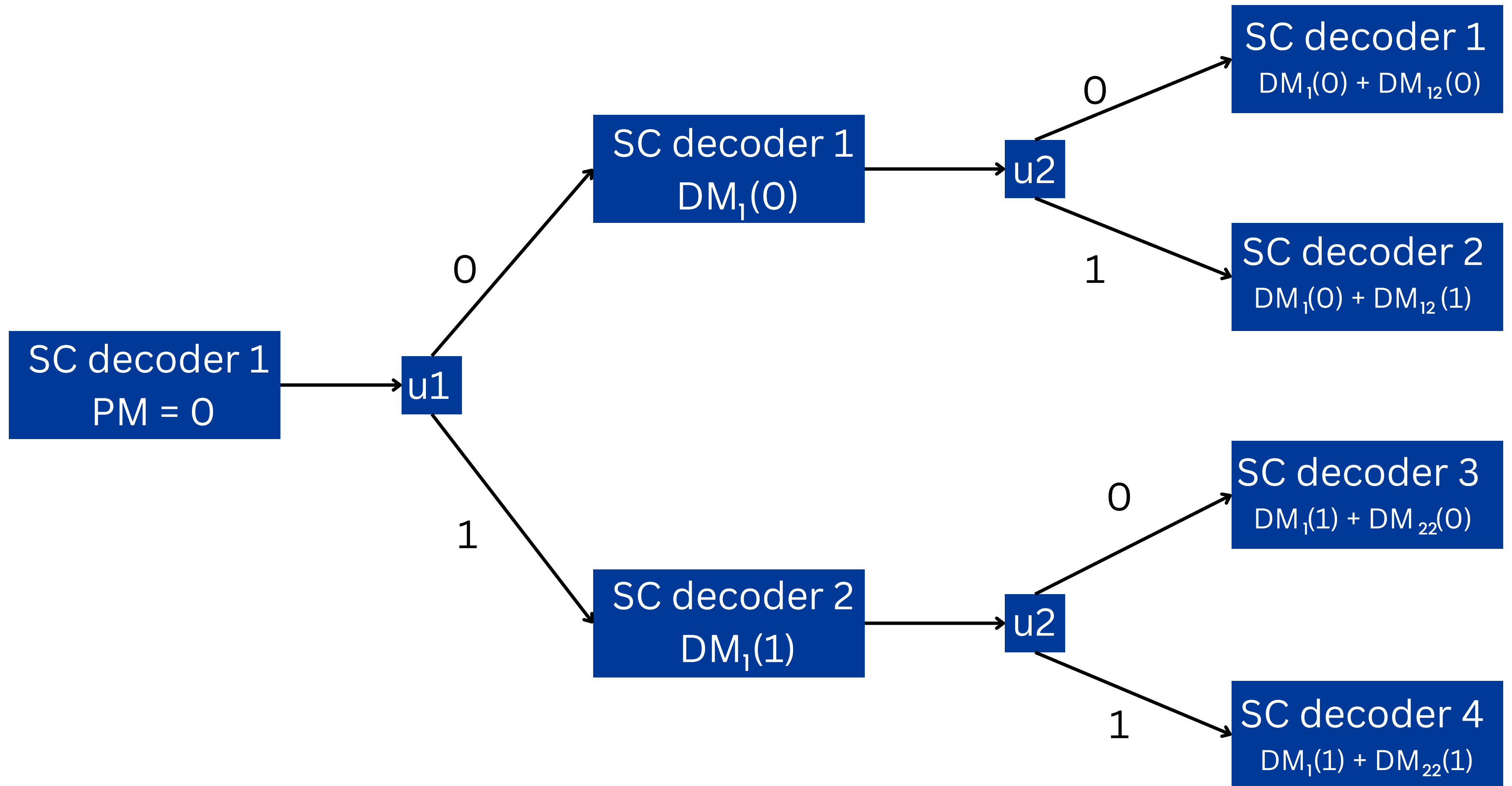
**Note:** If  $u_i$  is a frozen bit and  $L(u_i) < 0$ , then DM is also assigned.

## Path metric:

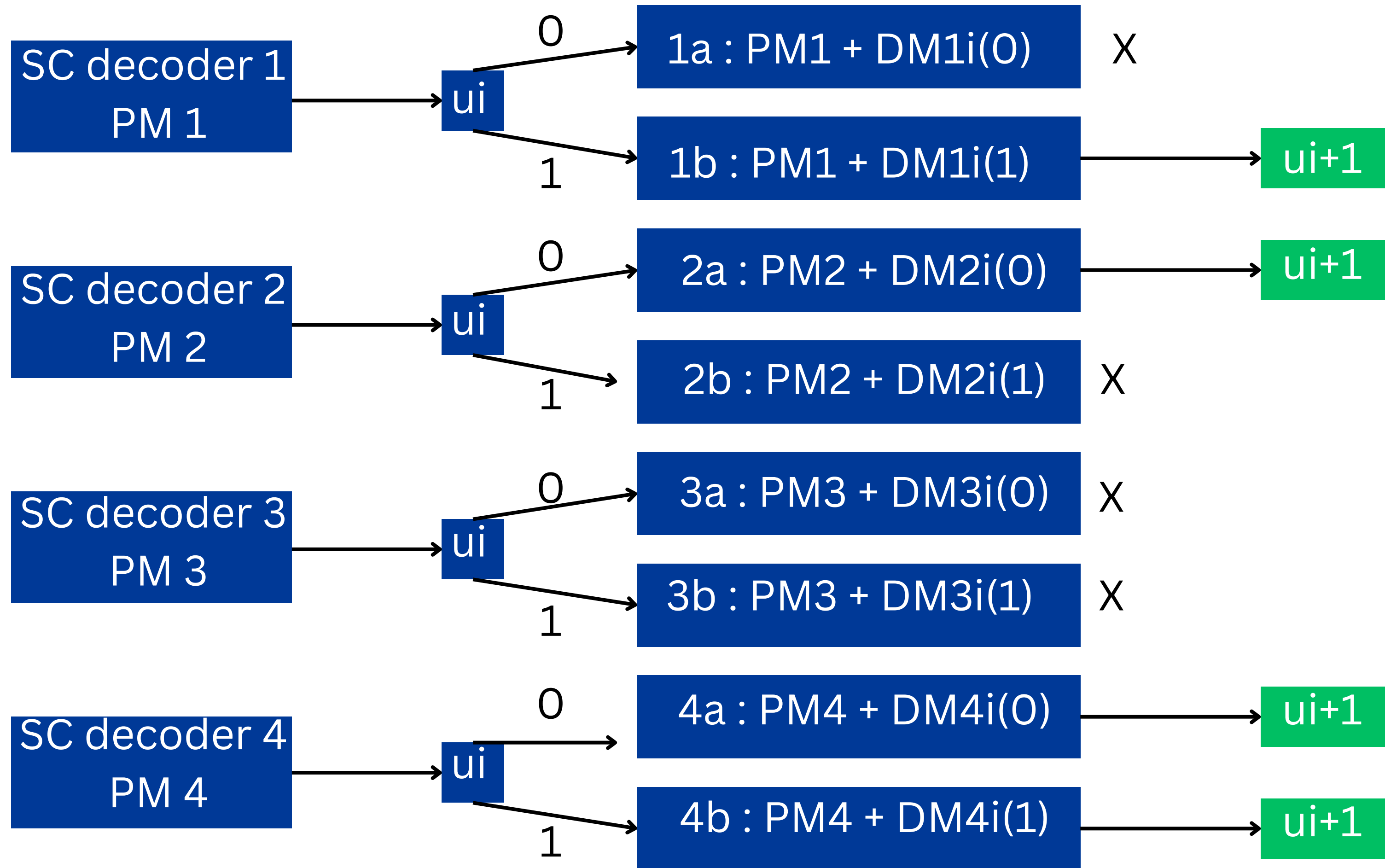
Sum of decision metrics for every path is called Path metric.

# Algorithm:

- Here we use as many SC decoders as our list size ( $L$ ) and run them together.
- We follow the same procedure as SC decoder for all the concurrent decoders except at the leaf.
- At the leaf we do following extra procedures as follows:
- We consider all possible estimated bits for a given belief
- We keep track of path metric in which we assign a penalty (absolute value of belief) for taking an opposite decision for a given belief.
- Then we sort and take the first  $L$  decoders having minimal path metrics.
- After we receive the  $L$  decoded codewords we perform a CRC check.







# Possible scenarios during CRC check on L decoded codewords

```
graph TD; A[Possible scenarios during CRC check on L decoded codewords] --> B[When none of the codewords yield zero remainder]; A --> C[When only 1 of the codeword yield zero remainder]; A --> D[When more than 1 codewords yield zero remainder]; B --> E[Choose codeword with minimum path metric]; C --> F[Select that codeword]; D --> G[Choose codeword with minimum path metric];
```

When none of the  
codewords yield zero  
remainder

Choose codeword  
with minimum path  
metric

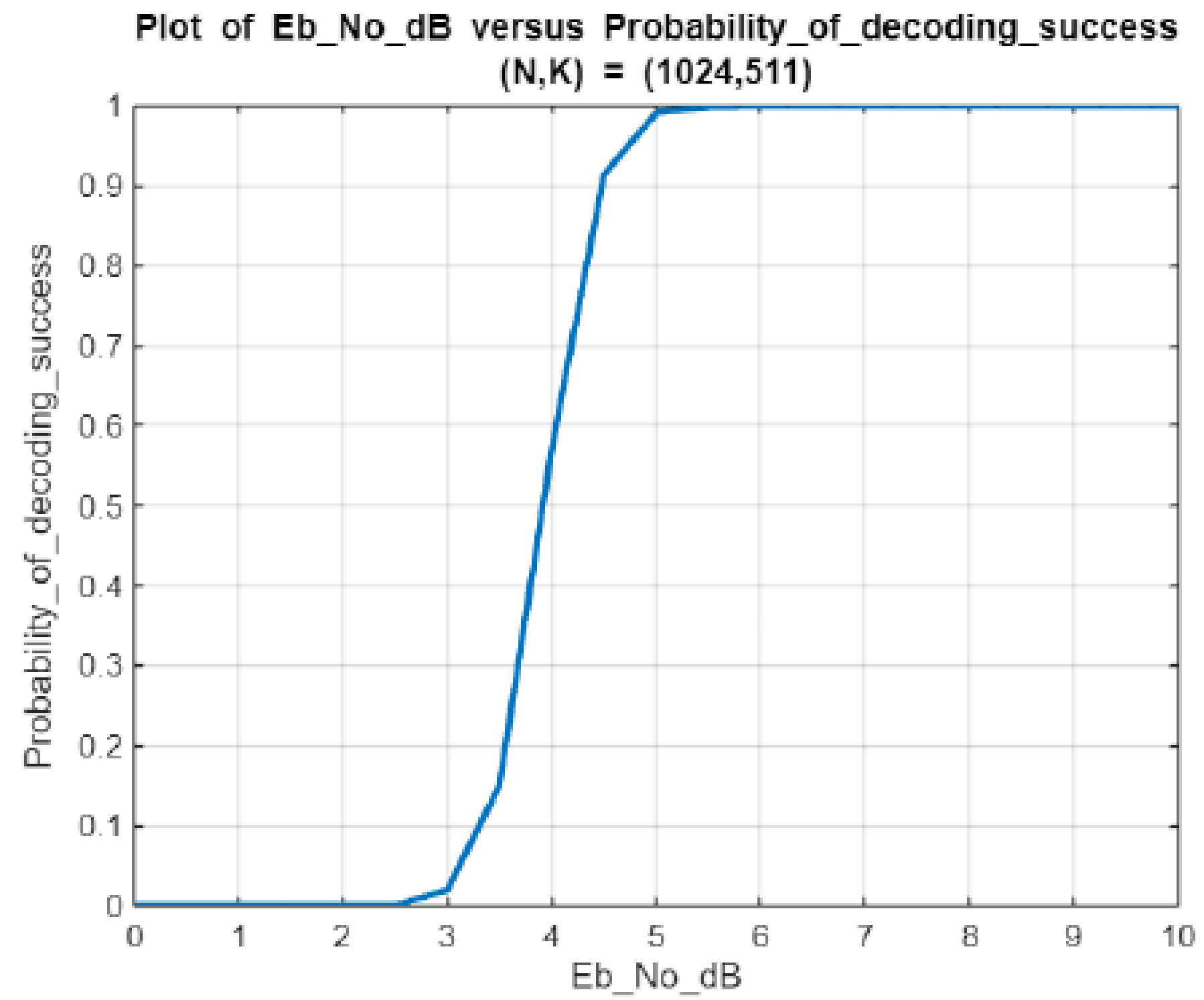
When only 1 of the  
codeword yield zero  
remainder

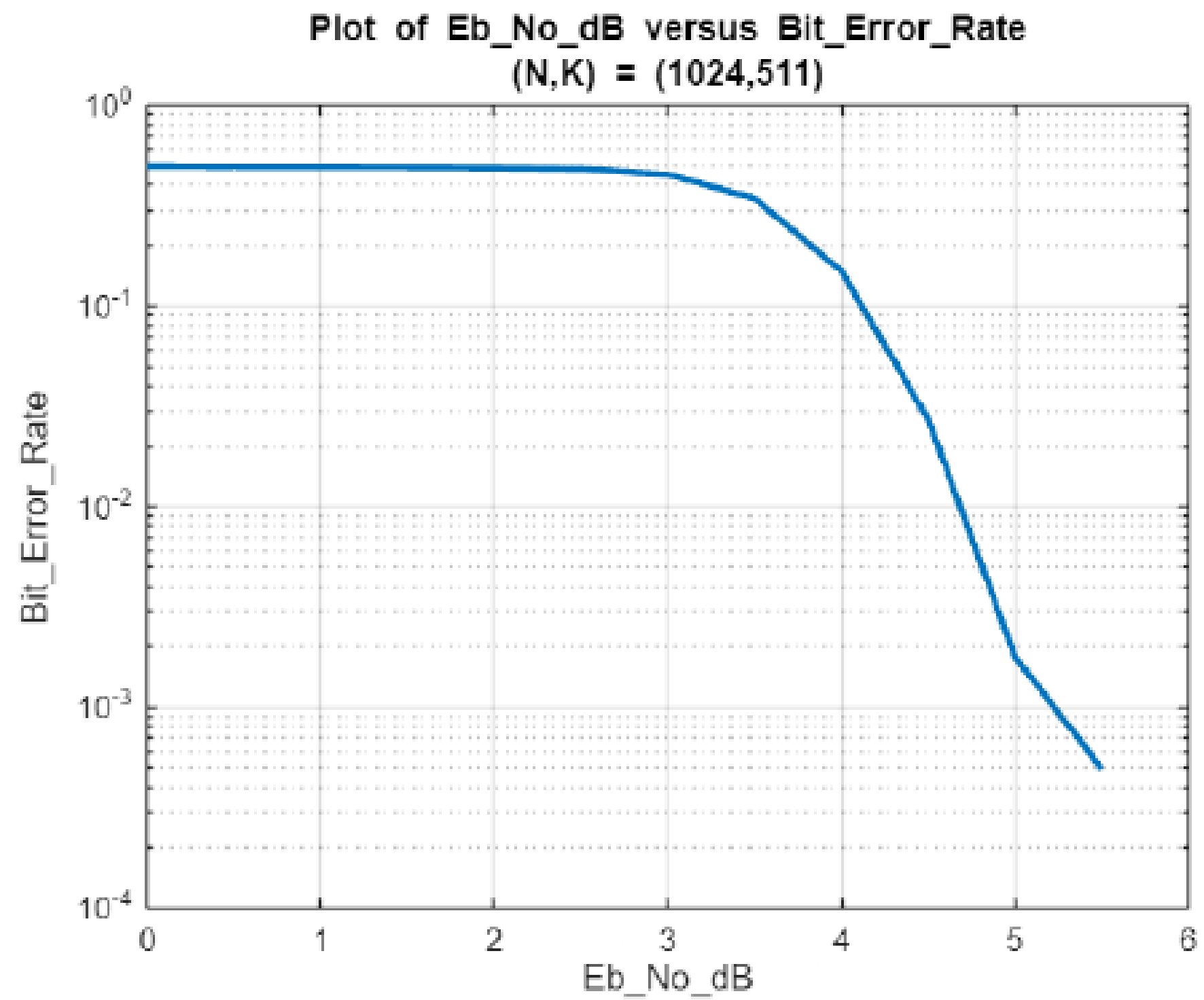
Select that codeword

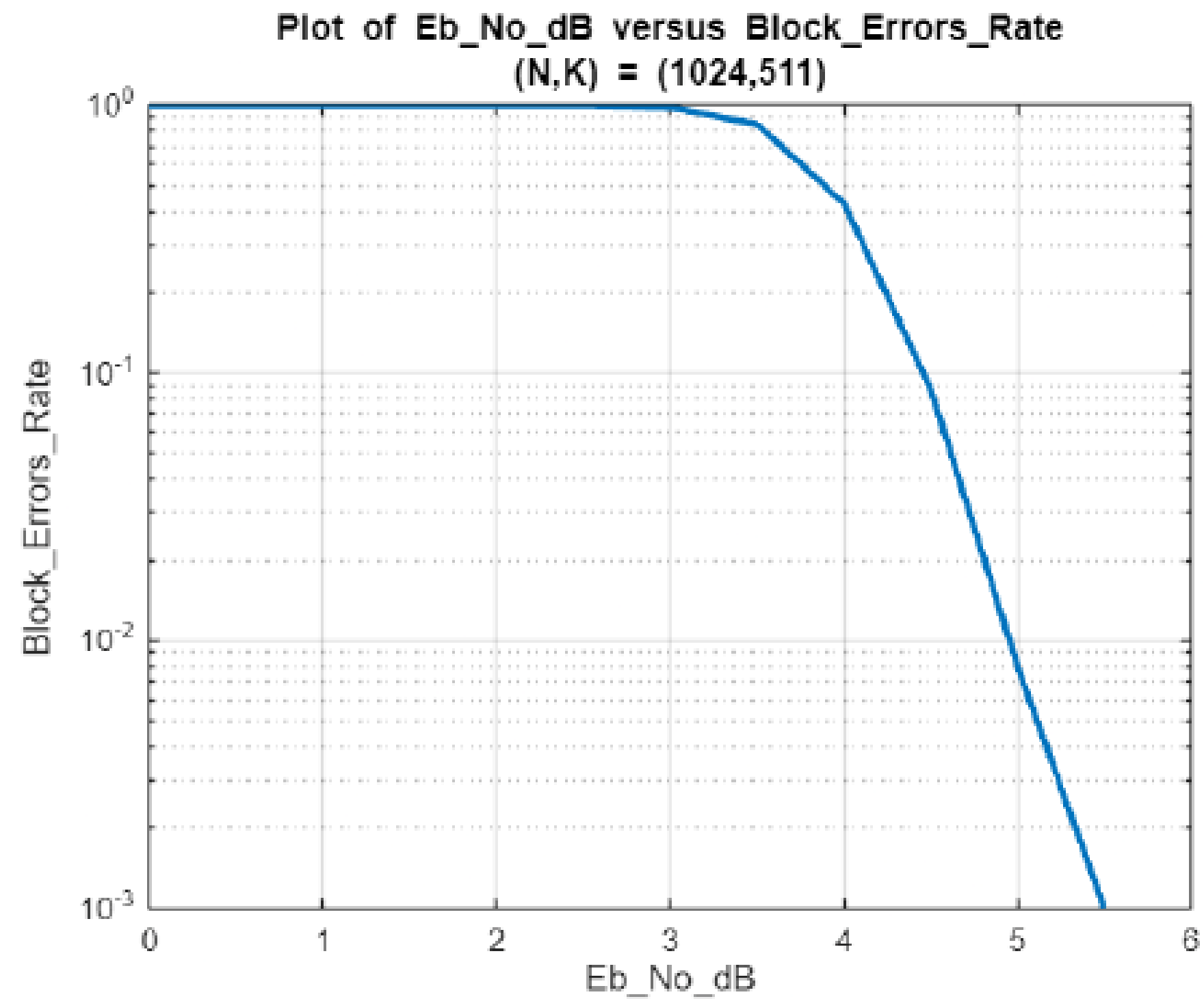
When more than 1  
codewords yield zero  
remainder

Choose codeword  
with minimum path  
metric

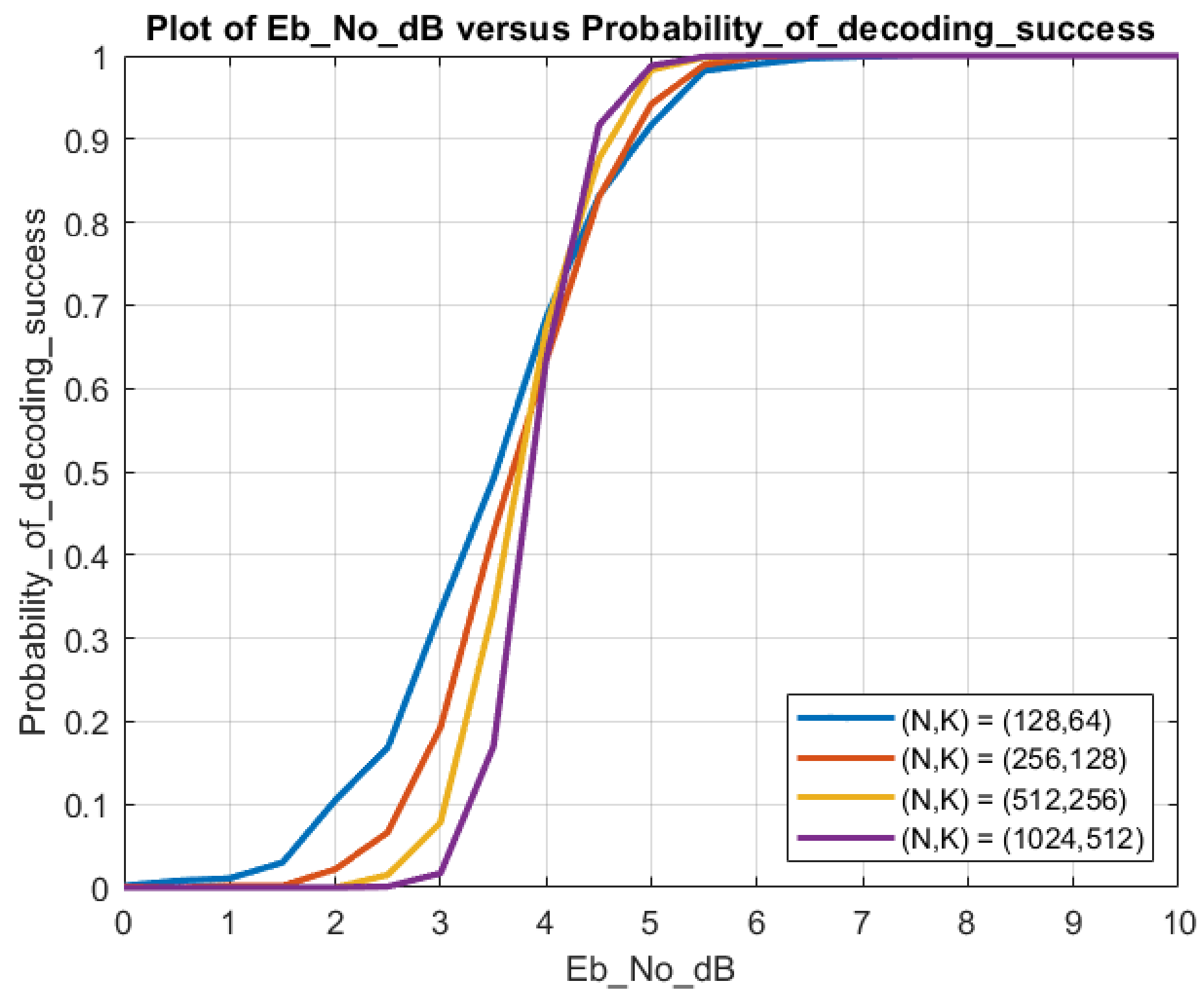
# **Simulating Outputs**



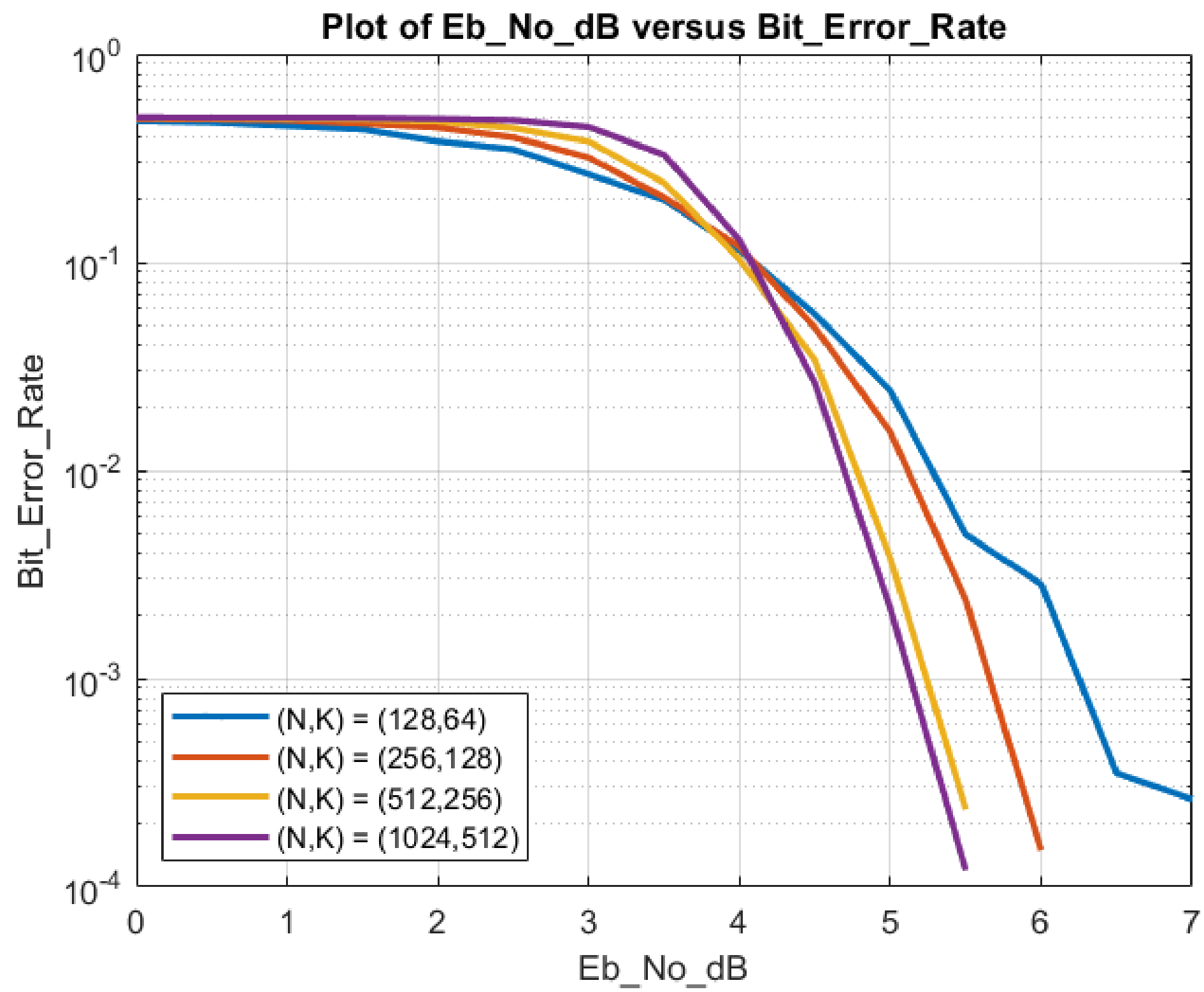


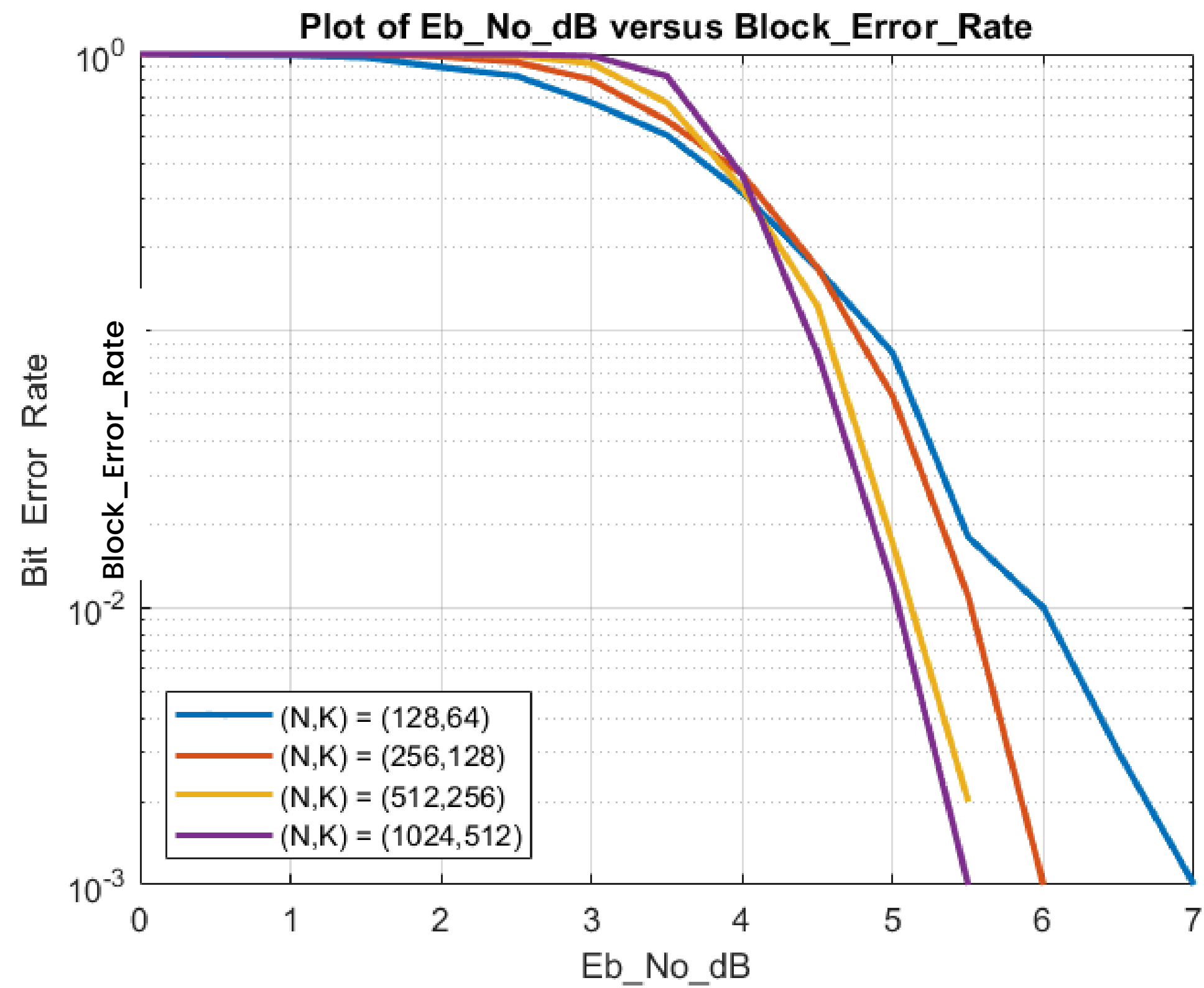


**Simulating for  
different  $(N,K)$ 's**

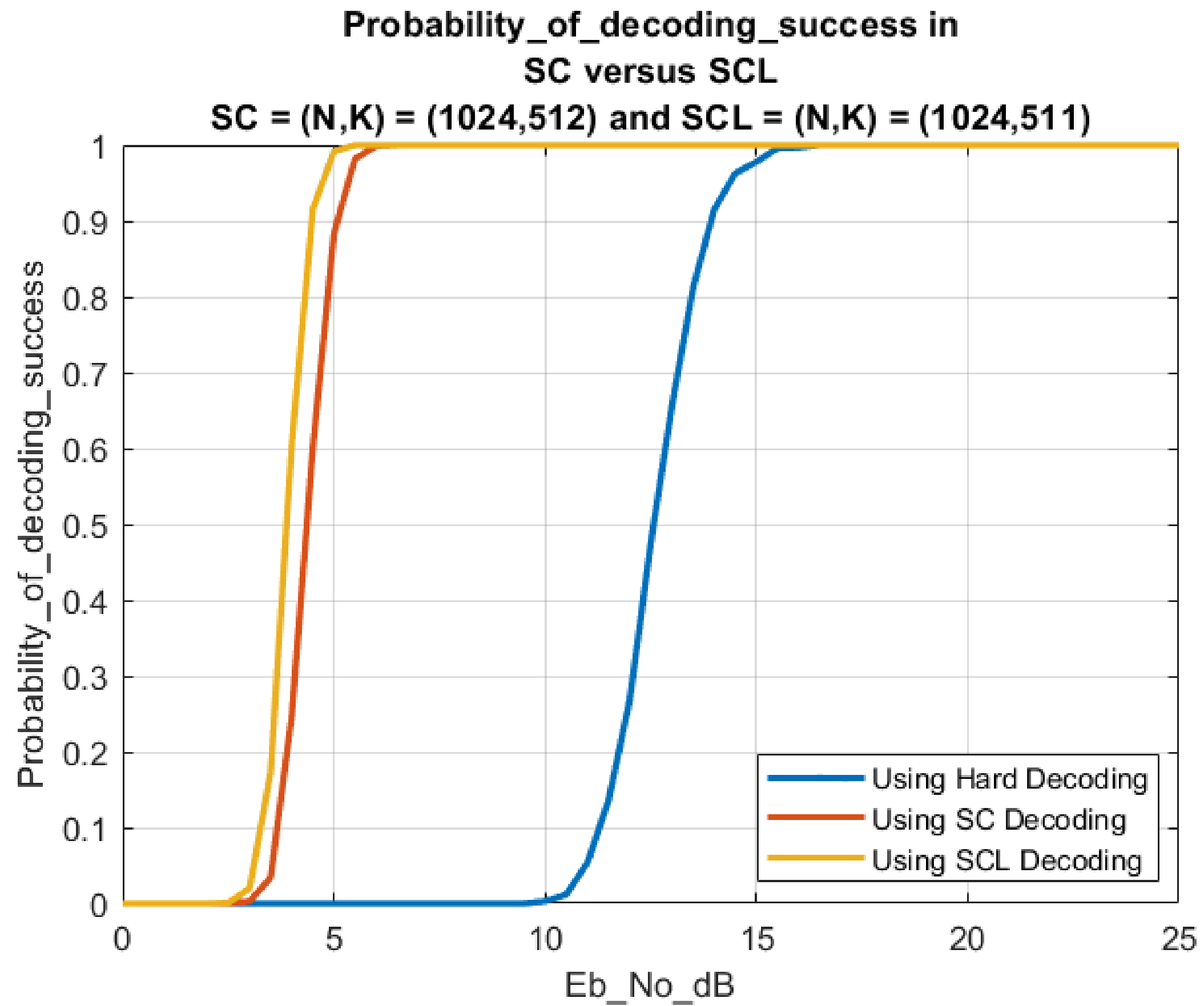


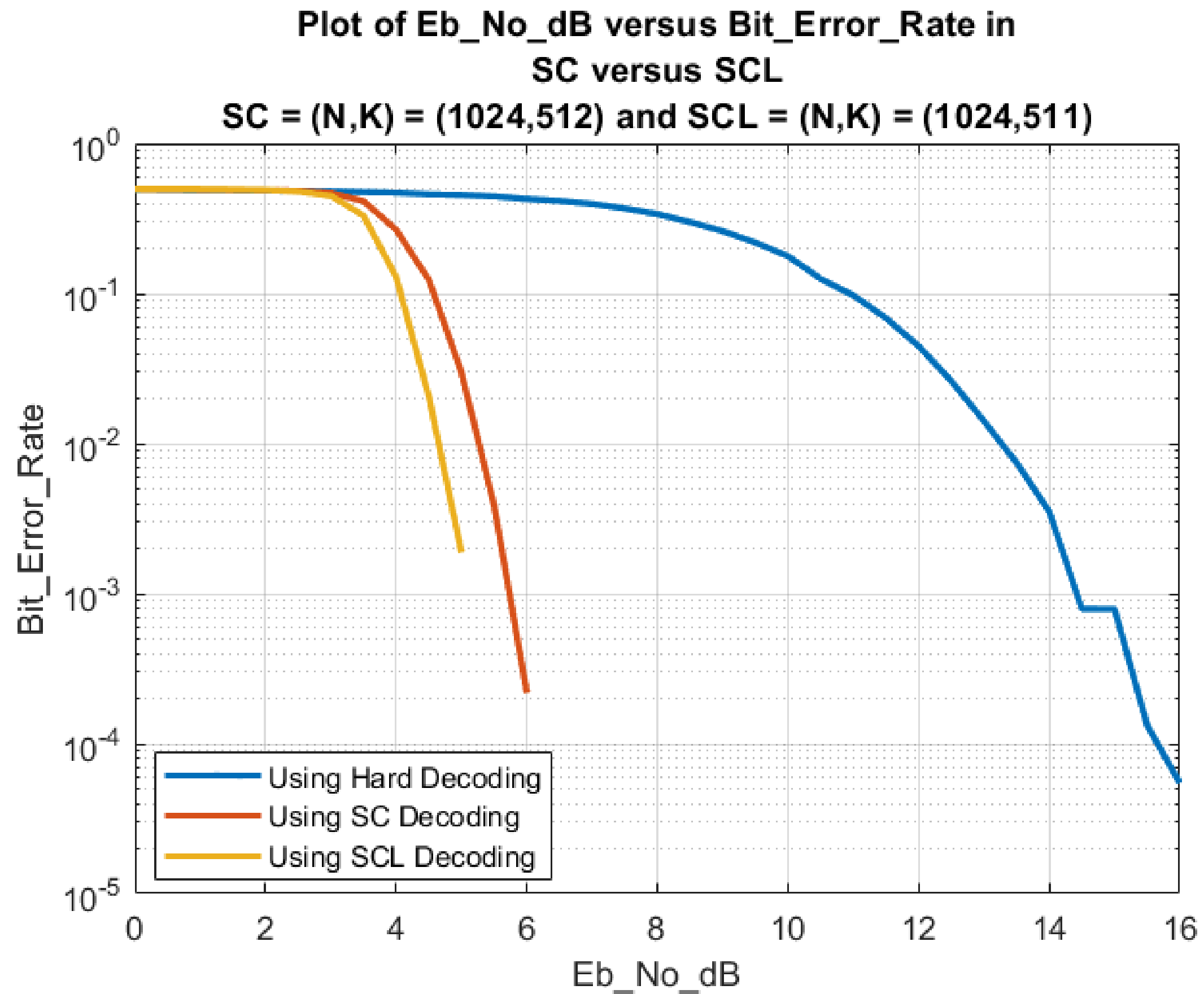


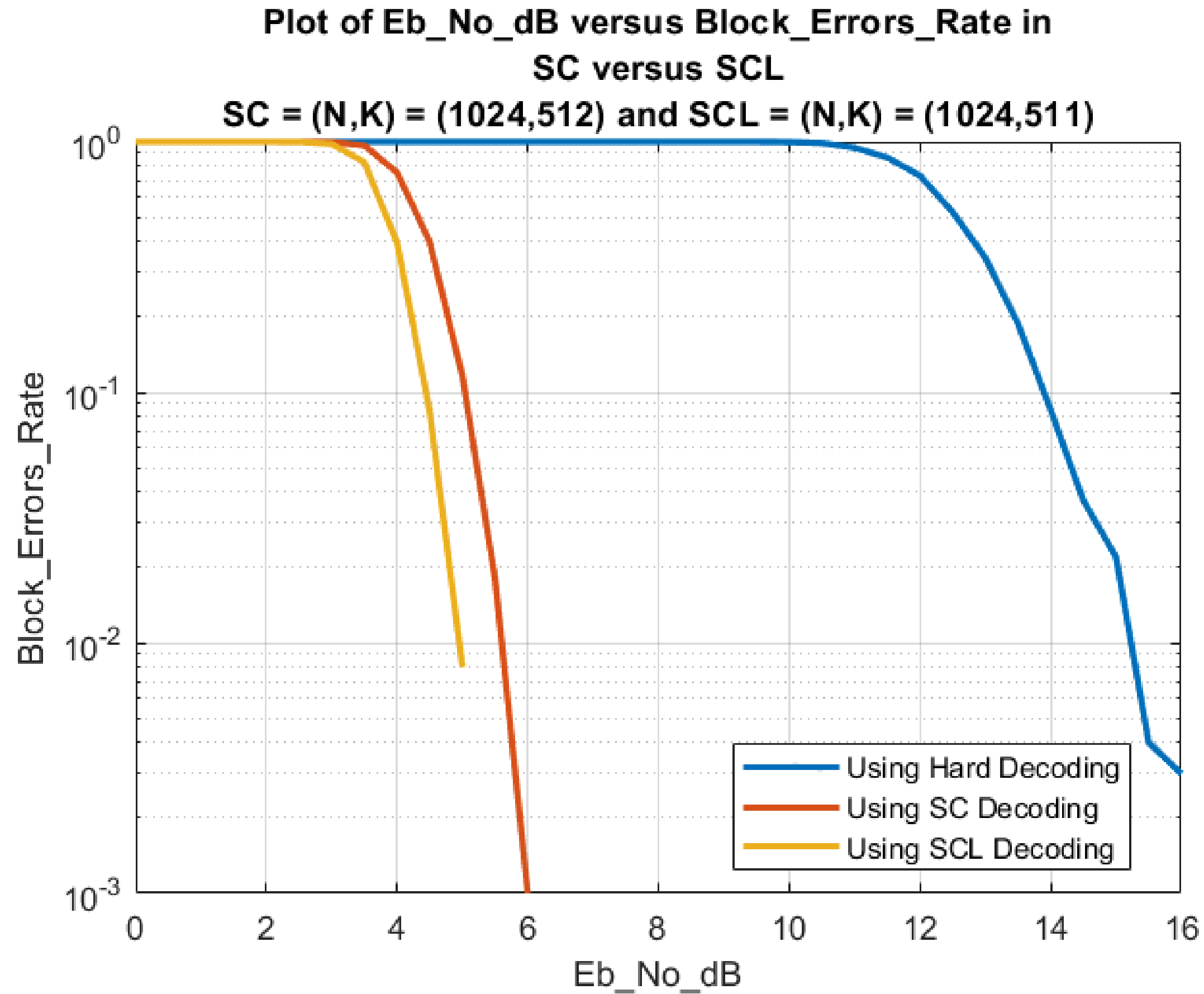




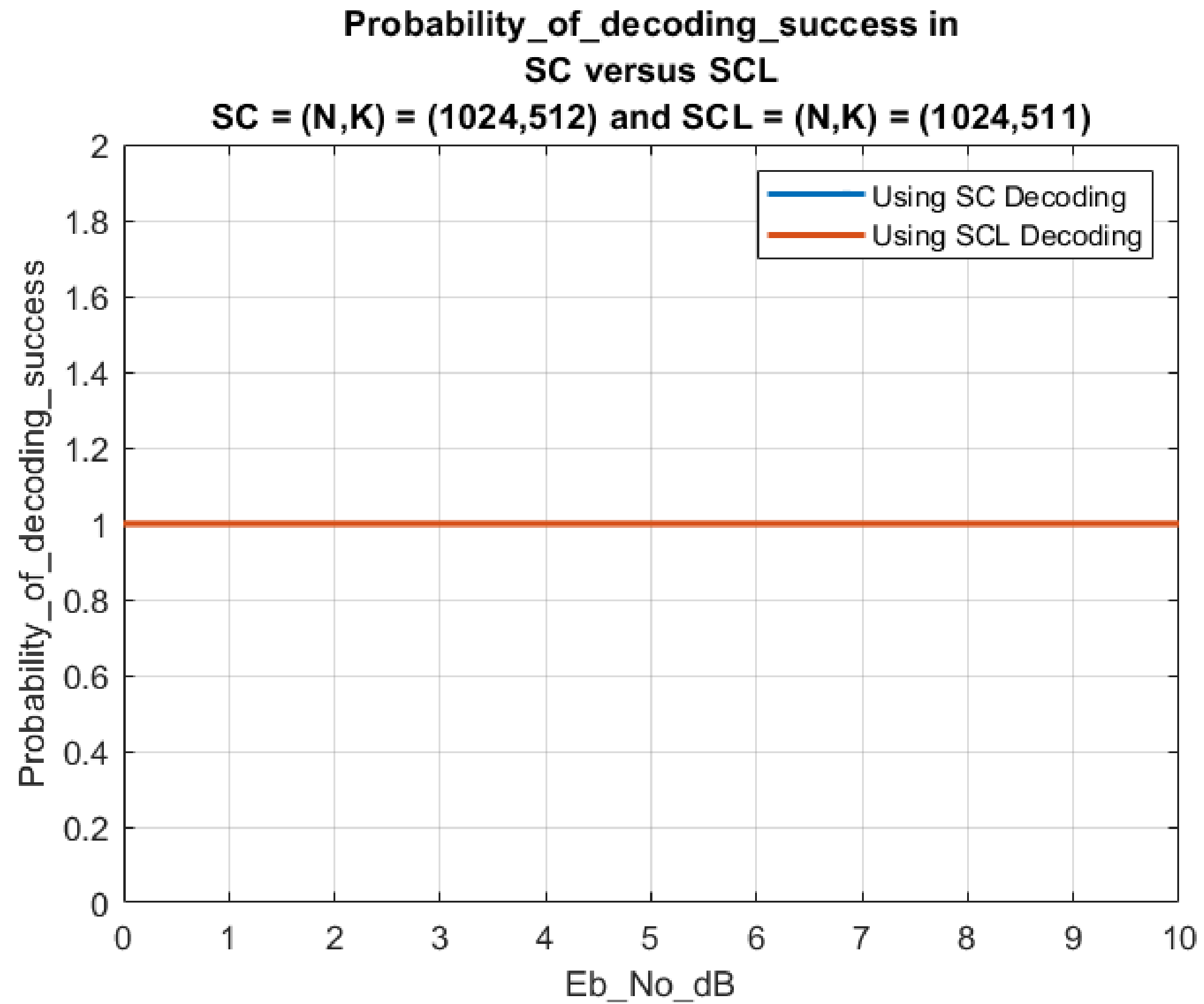
# **Decoder Comparison Outputs**



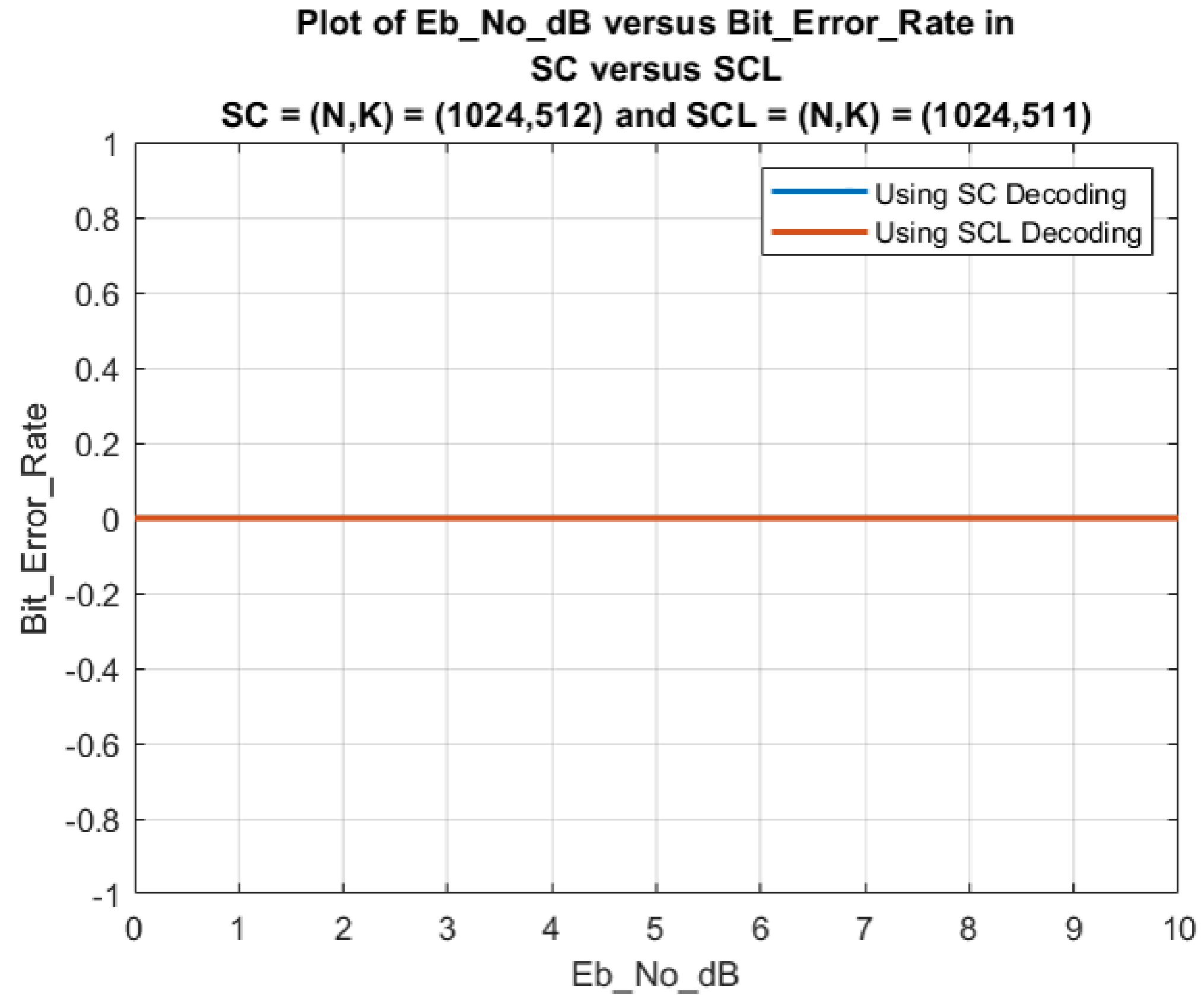


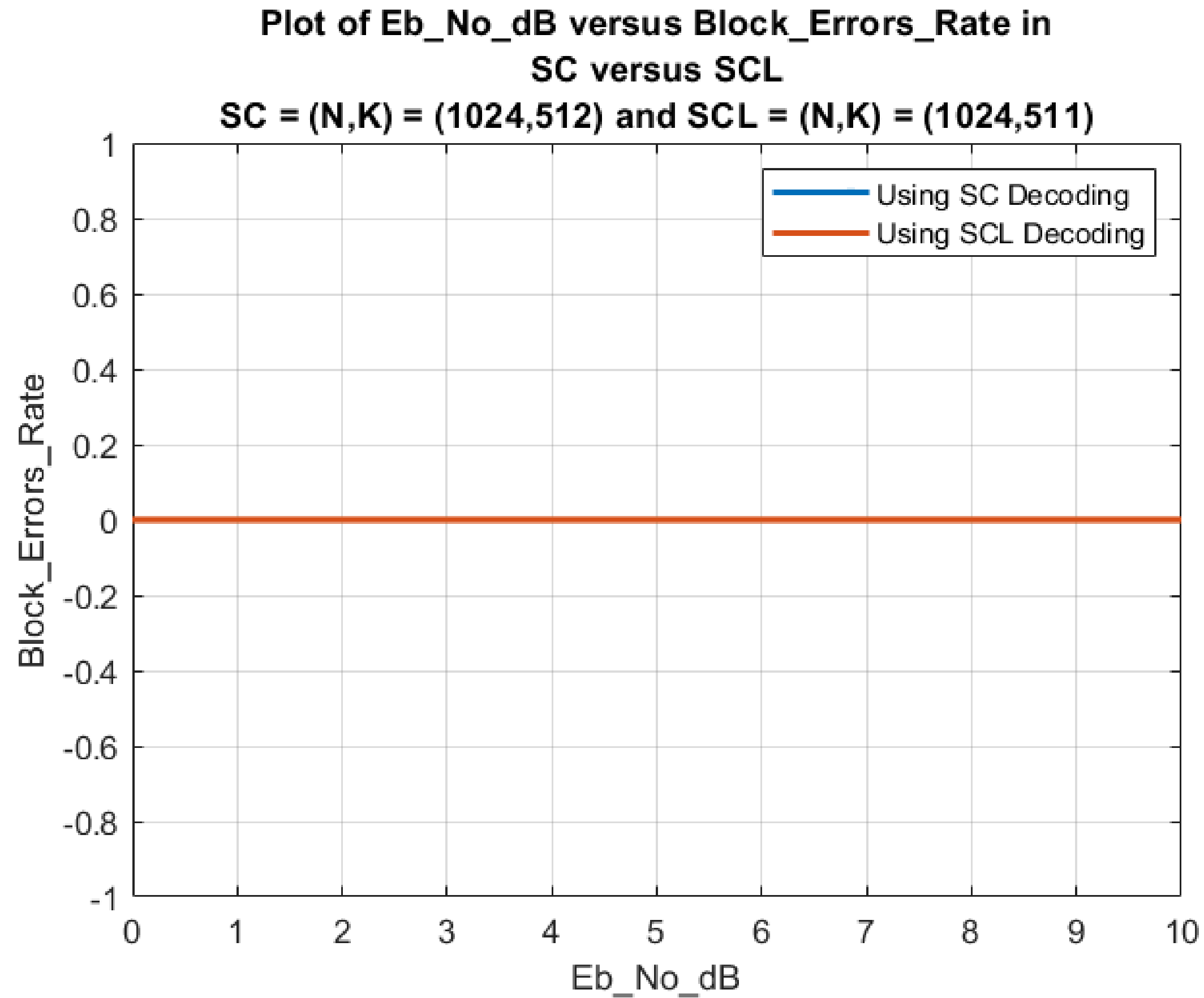


# Comparing Functionality Test









# Appendix

# SISO Decoder for SPC

Let us assume a Single Parity Check (SPC) Code with  $(N, K) = (3, 2)$

where,  $K$  = Number of message bits

$N$  = Number of encoded bits

Let message bits  $m = [m_1 \ m_2]$

Let code word  $c = [c_1 \ c_2 \ c_3]$

Let Received bits  $r = [r_1 \ r_2 \ r_3]$

Let us define the Beliefs for these Code word bits be, Beliefs =  $[l_1 \ l_2 \ l_3]$

Now, In SPC Code, If we know  $c_2$  and  $c_3$ , then the bit  $c_1$  is given by,

$$\therefore c_1 = c_2 \oplus c_3$$

Now, We define the Likelihood Ratio for bit  $c_i$ , where  $i \in N$  as,

$$\therefore \lambda_i = \frac{\text{pr}(c_i=0|r_i)}{\text{pr}(c_i=1|r_i)}$$

And so the Log-Likelihood Ratio for bit  $c_i$ , where  $i \in N$  is given by,

$$\therefore l_i = \ln(\lambda_i)$$

$$\therefore l_i = \ln\left(\frac{\text{pr}(c_i=0|r_i)}{\text{pr}(c_i=1|r_i)}\right)$$

Now Assume that, we know the probability of  $c_2$  being 1 is  $p_2$  and  $c_3$  being 1 is  $p_3$ .

So, The Probability of bit  $c_1 = 1$  is given by,

$$\therefore 1 - p_1 = (1 - p_2) \cdot p_3 + (1 - p_3) \cdot p_2$$

and, The Probability of bit  $c_1 = 0$  is given by,

$$\therefore p_1 = p_2 \cdot p_3 + (1 - p_2) \cdot (1 - p_3)$$

From the above two equations the Following Equation Holds true:

$$\therefore \frac{p_1 - (1 - p_1)}{p_1 + (1 - p_1)} = \frac{p_2 - (1 - p_2)}{p_2 + (1 - p_2)} \cdot \frac{p_3 - (1 - p_3)}{p_3 + (1 - p_3)}$$

$$\therefore \frac{1 - (\frac{1 - p_1}{p_1})}{1 + (\frac{1 - p_1}{p_1})} = \frac{1 - (\frac{1 - p_2}{p_2})}{1 + (\frac{1 - p_2}{p_2})} \cdot \frac{1 - (\frac{1 - p_3}{p_3})}{1 + (\frac{1 - p_3}{p_3})}$$

Now, Let us define Extrinsic Log-Likelihood ratio,  $l_{\text{ext},i} = \ln(\frac{p_i}{1 - p_i})$ , , where  $i \in N$

Therefore, above Equation can be written as,

$$\therefore \frac{1 - e^{-l_{\text{ext},1}}}{1 + e^{-l_{\text{ext},1}}} = \frac{1 - e^{-l_2}}{1 + e^{-l_2}} \cdot \frac{1 - e^{-l_3}}{1 + e^{-l_3}}$$

Now, We know that,  $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{1 - e^{-2x}}{1 + e^{-2x}}$

Thus, the above Equation becomes,

$$\therefore \tanh\left(\frac{l_{\text{ext},1}}{2}\right) = \tanh\left(\frac{l_2}{2}\right) \cdot \tanh\left(\frac{l_3}{3}\right)$$

Function Analysis of  $\tanh(x)$  :

$$\text{Let } f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Now replacing  $x$  by  $-x$ ,

$$f(-x) = \frac{e^{-x} - e^x}{e^{-x} + e^x}$$

$$f(-x) = - \frac{e^{-x} - e^x}{e^{-x} + e^x}$$

$$f(-x) = - f(x)$$

$$f(x) = - f(-x)$$

Hence,  $\tanh(x)$  is an odd function:

Here, we observe that,

- $x < 0 \Rightarrow \tanh(x) < 0$
- $x > 0 \Rightarrow \tanh(x) > 0$

The above results shows that  $\tanh(x)$  follows  $\text{sgn}(x)$  function  
So, we have above set of Equations,

$$\therefore \text{sgn}(l_{\text{ext},1}) = \text{sgn}(l_2) \cdot \text{sgn}(l_3)$$

$$\therefore \tanh\left(\frac{|l_{\text{ext},1}|}{2}\right) = \tanh\left(\frac{|l_2|}{2}\right) \cdot \tanh\left(\frac{|l_3|}{2}\right)$$

$$\therefore \ln\left(\tanh\left(\frac{|l_{\text{ext},1}|}{2}\right)\right) = \ln\left(\tanh\left(\frac{|l_2|}{2}\right)\right) + \ln\left(\tanh\left(\frac{|l_3|}{2}\right)\right)$$

Let,  $f(x) = \left|\ln\left(\tanh\frac{|x|}{2}\right)\right|$ , where  $x > 0$ ;

Hence,  $f^{-1}(x) = f(x)$

$$\therefore f(|l_{\text{ext},1}|) = f(|l_2|) + f(|l_3|)$$

$$\therefore |l_{\text{ext},1}| = f(f(|l_2|) + f(|l_3|))$$

Here, Intrinsic Beliefs are :  $l_1, l_2, l_3$

Here, Extrinsic Beliefs are :  $l_{\text{ext},1}, l_{\text{ext},2}, l_{\text{ext},3}$

Also,  $f(x)$  is a non-linear function.

Thus, the Expression  $f(l_2) + f(l_3)$  is approximately equal to  $f(\min(|l_2|, |l_3|))$

So, The Min-sum approximation is given by :

$$\therefore |l_{\text{ext}_1}| = \min(|l_2|, |l_3|)$$

$$\therefore \text{sgn}(l_{\text{ext}_1}) = \text{sgn}(l_2) \cdot \text{sgn}(l_3)$$



# SISO Decoder for Repetition Code

## Log Likelihood Ratio for $n = 3$ Repetition code

$\mathbf{c} = [c_1 \ c_2 \ c_3]$  Code\_word

$\mathbf{r} = [r_1 \ r_2 \ r_3]$  Received\_word

$$\text{pr}(c_1=0|r_1) = \frac{f(r_1|c_1=0) \cdot \text{pr}(c_1=0)}{f(r_1)}$$

$$\text{pr}(c_1=1|r_1) = \frac{f(r_1|c_1=1) \cdot \text{pr}(c_1=1)}{f(r_1)}$$

Likelihood Ratio:

$$\frac{\text{Pr}(c_1=0|r_1)}{\text{Pr}(c_1=1|r_1)} = \frac{f(r_1|c_1=0)}{f(r_1|c_1=1)}$$

Where  $f(x)$  is the probability density function for the Gaussian distribution:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

When  $c_1=0$ , the symbol  $s$  will be  $+1$  and hence the received bit  $r_1 = s + n$ :

$$r_1 = 1 + n$$

So:

$$\frac{f(r_1|c_1=0)}{f(r_1|c_1=1)} = \frac{\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(r_1-1)^2}{2\sigma^2}}}{\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(r_1+1)^2}{2\sigma^2}}}$$

Taking the logarithm on both sides:

$$\log \left( \frac{\Pr(c_1=0|r_1)}{\Pr(c_1=1|r_1)} \right) = \log \left( e^{\frac{2r_1}{\sigma^2}} \right) = \frac{2r_1}{\sigma^2}$$

Output Log-Likelihood Ratio (LLR) SISO Decoder:

Belief vector  $\rightarrow [L_1 \ L_2 \ L_3]$

$$L_i = \log \left( \frac{\Pr(c_i=0|r_1, r_2, r_3)}{\Pr(c_i=1|r_1, r_2, r_3)} \right)$$

$L_1$ :

$$\frac{f(r_1, r_2, r_3|c_1=0) \cdot \Pr(c_1=0)}{\Pr(r_1, r_2, r_3)}$$

Likelihood ratio of  $L_1$ :

$$\frac{f(r_1, r_2, r_3 | c_1=0)}{f(r_1, r_2, r_3 | c_1=1)}$$

When  $c_1=0$  and the output from BPSK is  $[+1 \ +1 \ +1]$ , then:

$$r_1 = 1 + N_1(0, \sigma^2)$$

$$r_2 = 1 + N_2(0, \sigma^2)$$

$$r_3 = 1 + N_3(0, \sigma^2)$$

$$\frac{e^{-\frac{(r_1-1)^2}{2\sigma^2}} \cdot e^{-\frac{(r_2-1)^2}{2\sigma^2}} \cdot e^{-\frac{(r_3-1)^2}{2\sigma^2}}}{e^{-\frac{(r_1+1)^2}{2\sigma^2}} \cdot e^{-\frac{(r_2+1)^2}{2\sigma^2}} \cdot e^{-\frac{(r_3+1)^2}{2\sigma^2}}}$$

Taking log:

$$L_1 = (r_1 + r_2 + r_3) \cdot \frac{2}{\sigma^2}$$

$L_i = (r_1 + r_2 + r_3) \cdot \frac{2}{\sigma^2}$ , where we set the factor  $\frac{2}{\sigma^2}$  as 1 for  $L_1$ .  
For  $L_1$ ,  $r_1$  is intrinsic and  $r_2, r_3$  are extrinsic.

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**Thank You!**