Optimizing Flash based Storage Systems

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- Lifetime
- Reliability
- Latency
- Throughput

Projects

- Reliability/Latency/Throughput: Error Correction Code (ECC) Parallelization and Incremental Redundancy
- Lifetime: Channel Estimation and Write Voltage Optimization

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Approaching Capacity Using Incremental Redundancy Without Feedback

Haobo Wang, Sudarsan V. S. Ranganathan, and Richard Wesel

Motivation/Application for Storage

- (Latency/Throughput) How to accelerate ECC for Flash?

Use parallel short codes to replace a long codeword!

- (Reliability) How to recover the data from a failed codeword more efficiently?

Lower the rate of the codeword adaptively!

Outline

- **Previous work**: Approaching Capacity with Short Blocklengths using Incremental Redundancy and ACK/NACK Feedback [Vakilinia et al. TCOM 2016]
- **New Idea**: Approaching Capacity using Many Short-blocklength Codes with Incremental Redundancy in Parallel *Without Feedback*
  - Concept
  - Design methods and design examples

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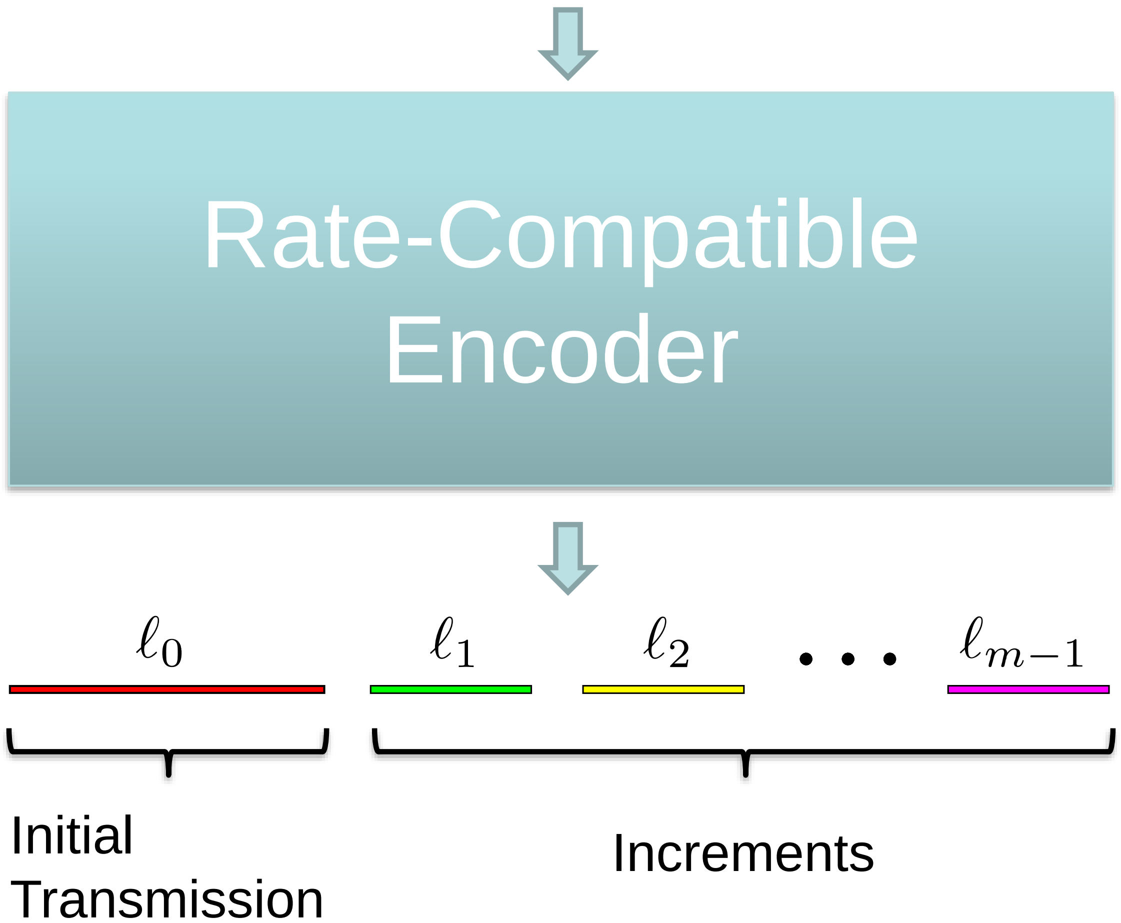
A Rate-compatible Encoder

k bits of user information



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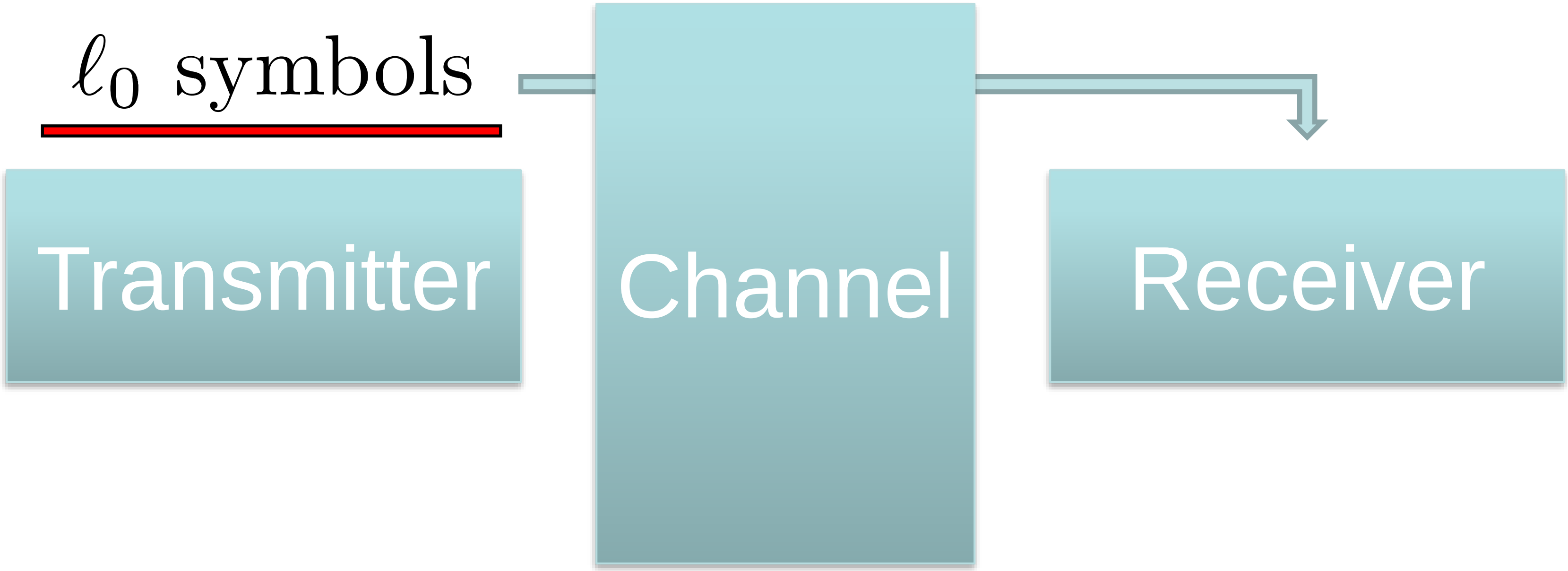
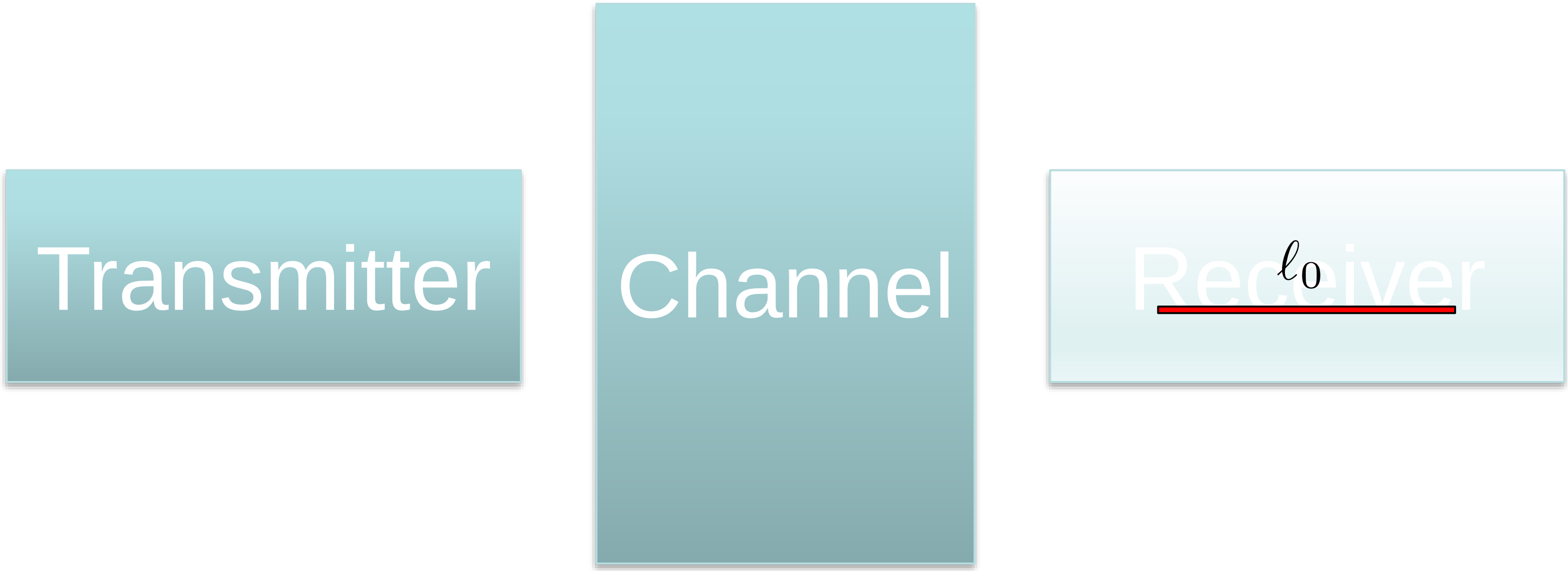
Incremental Redundancy with Feedback



Incremental Redundancy with Feedback



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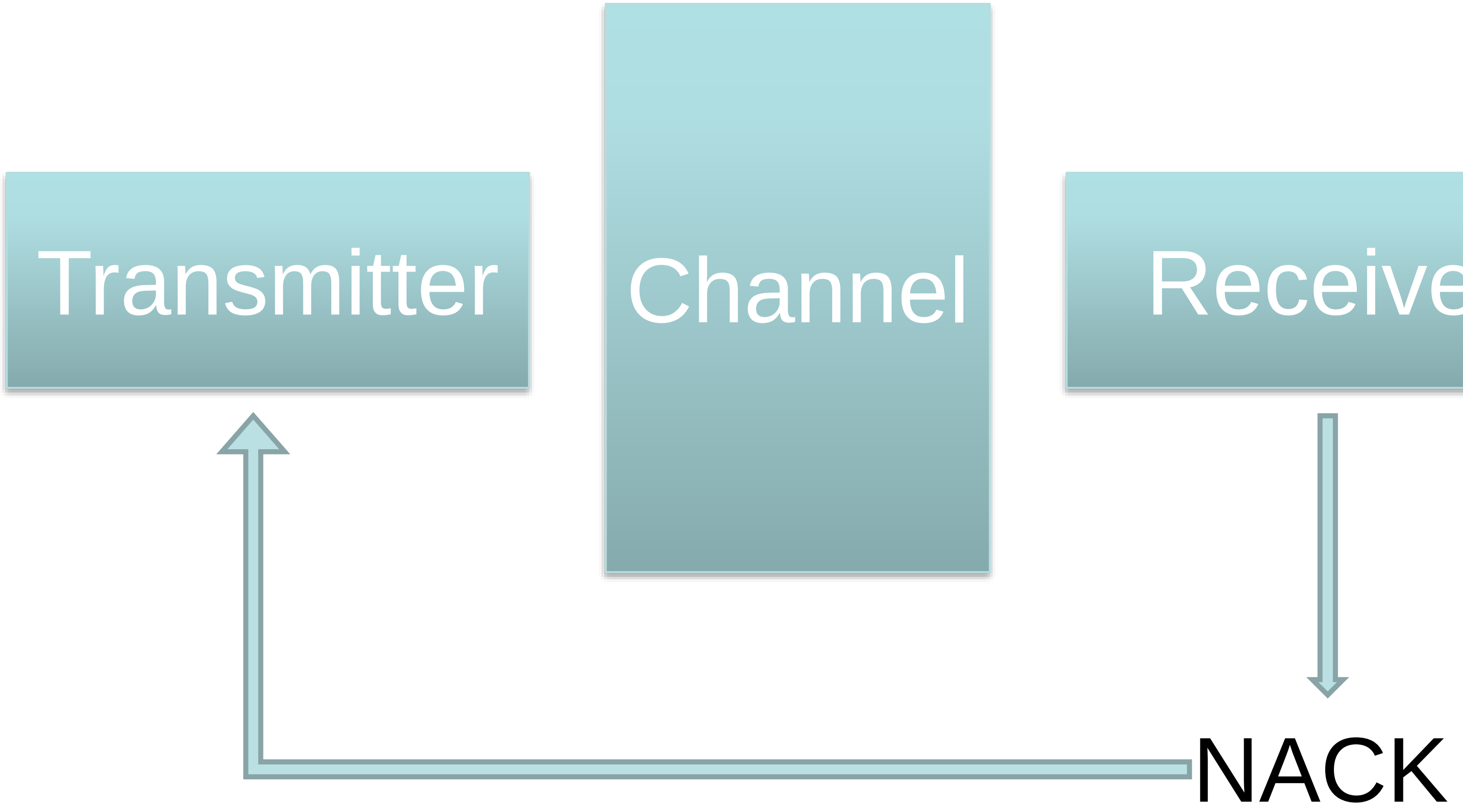

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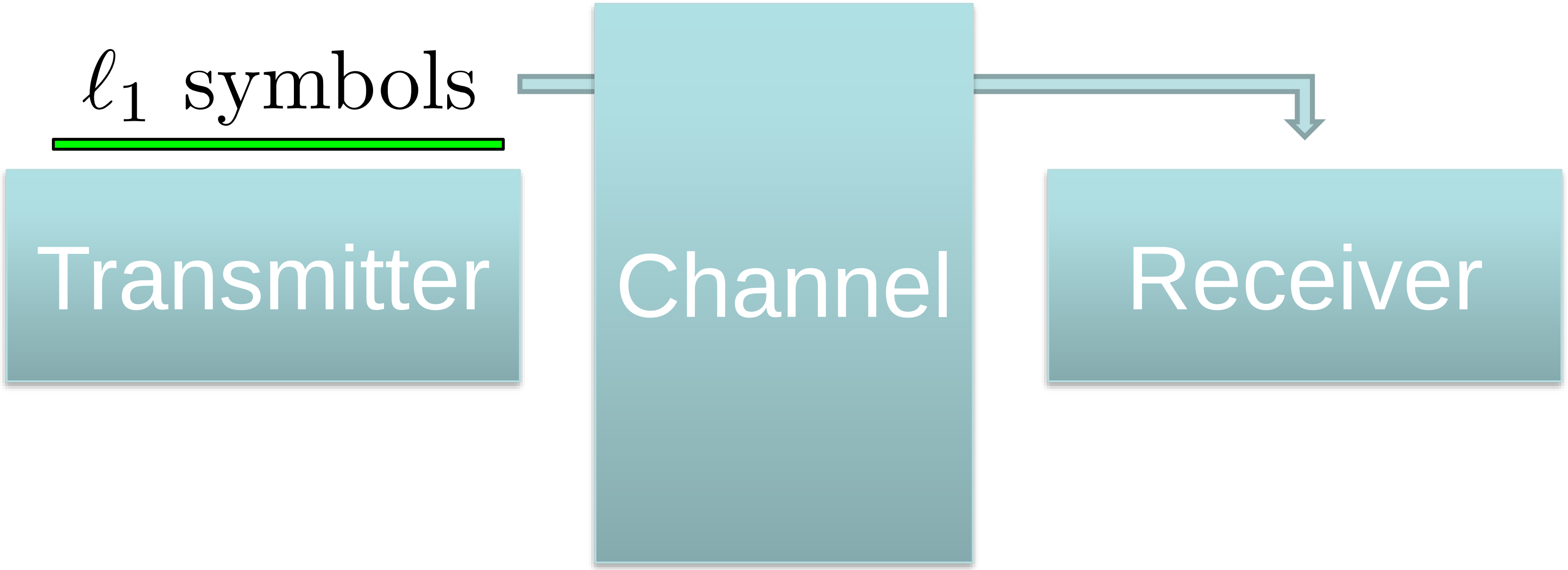
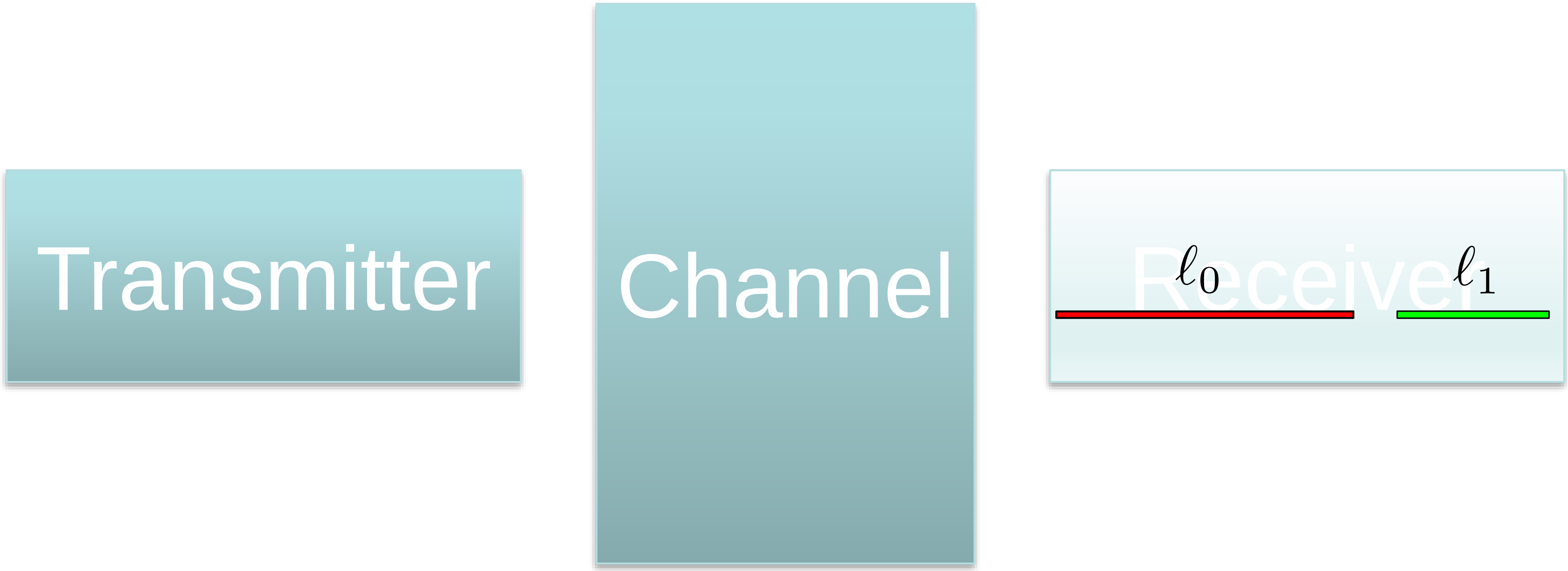
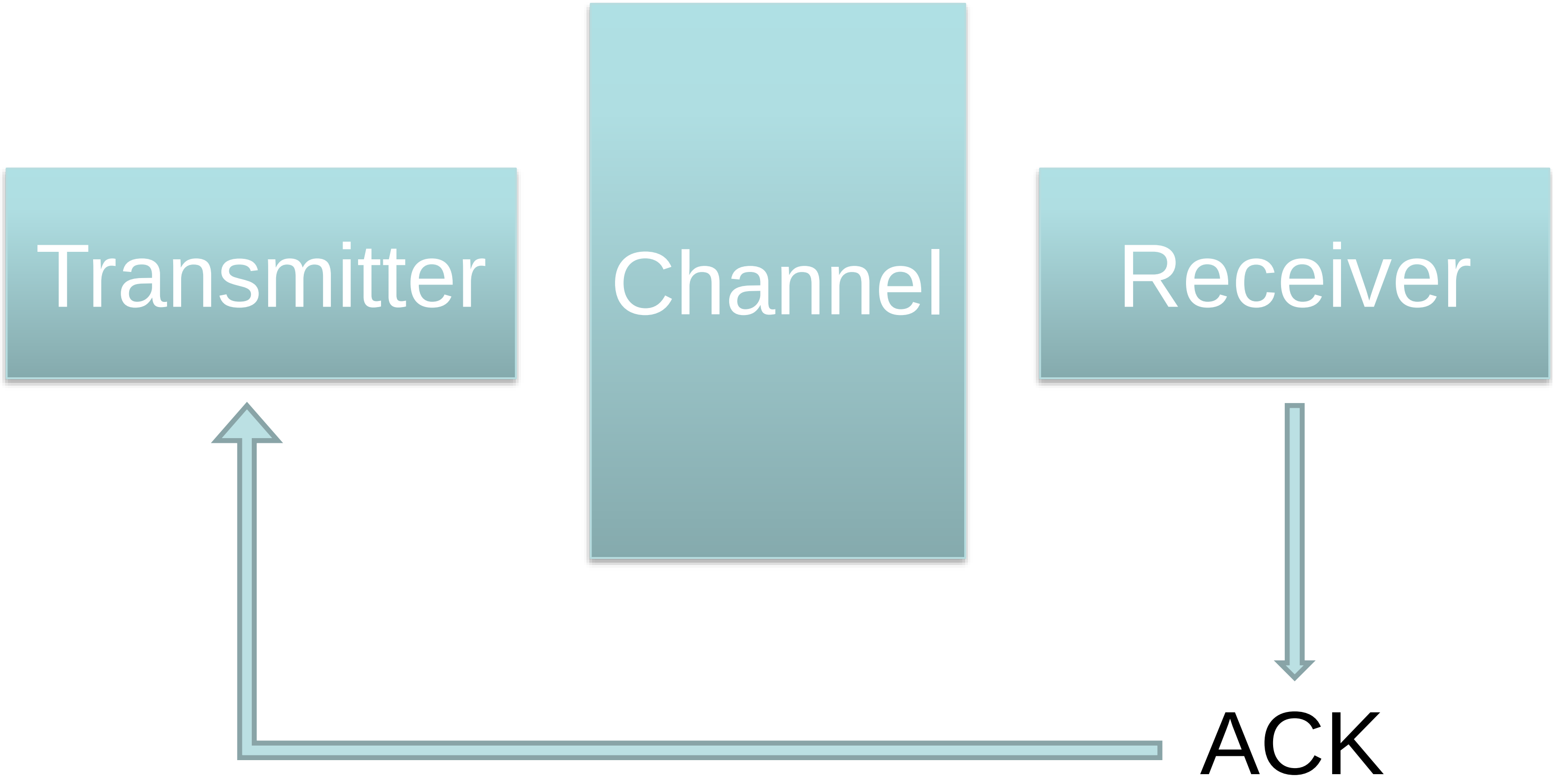


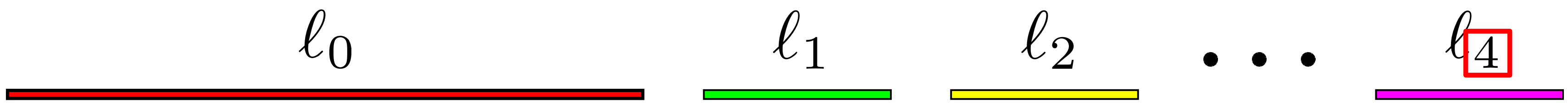
Incremental Redundancy with Feedback



Incremental Redundancy with Feedback



Variable-length Code Parameter in This Work



$$\ell_1 = \ell_2 = \ell_3 = \ell_4 = \ell_\Delta$$

$$R_t^{(FB)} = \frac{k(1 - \epsilon_{FB})}{l_0 + \beta_{FB}\ell_\Delta}$$

In this presentation, we will compare our feedback-free design against corresponding constant-increment-size feedback codes.

Keep in mind

- In general, a VL error correction code (ECC) with feedback has a higher rate than a feedforward ECC at comparable block length.
- We want to approach the rate of the feedback scheme without feedback.

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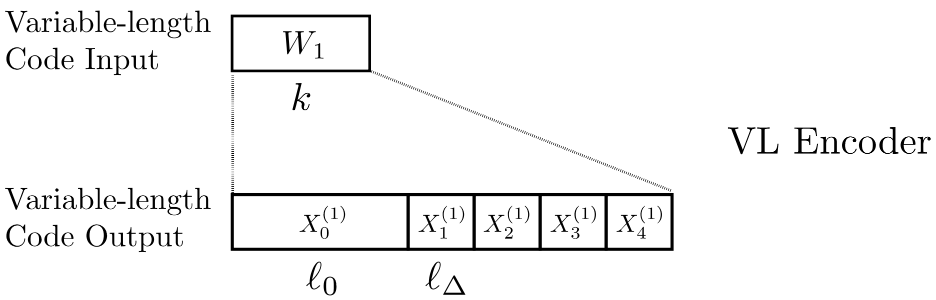
Principal Concept

- We use many VL codewords in parallel.
- Send the highest-rate part of each VL codeword. Some VL codewords need increments.
- From ergodicity, we know the total amount of redundancy needed by all the codewords.
- We use ***inter-frame coding [Zeineddine et al. JSAC 2016]*** to linearly encode the increments
  - Deliver exactly the right amount of redundancy for each VL codeword.
  - We expand the analysis to any point-to-point channel, and design actual codes.

Inter-frame Code [Zeineddine et al. JSAC 2016]



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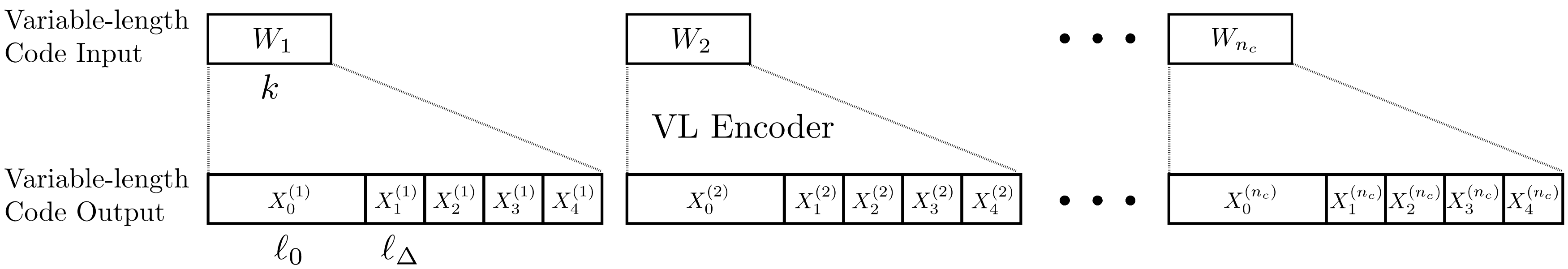

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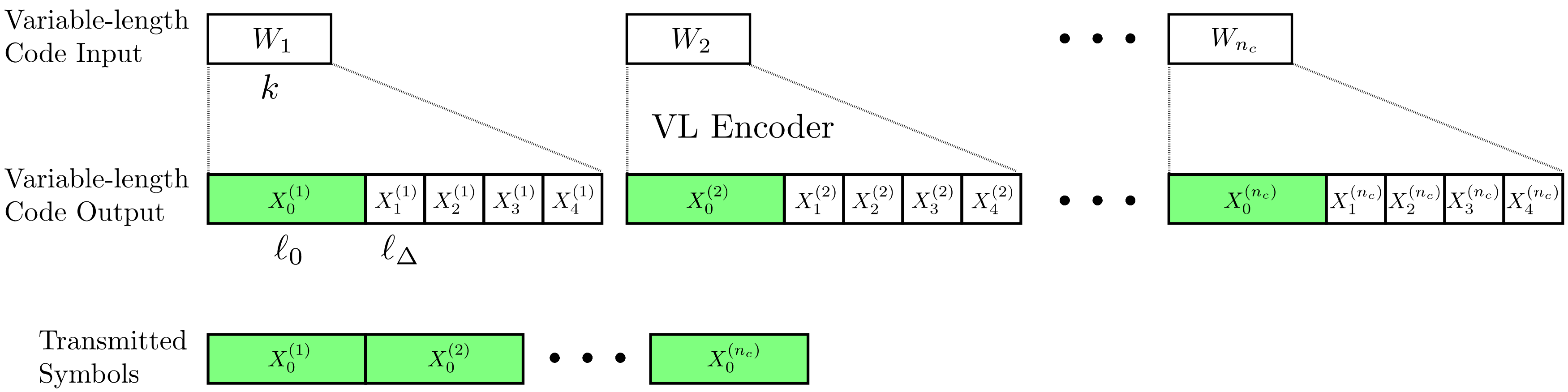

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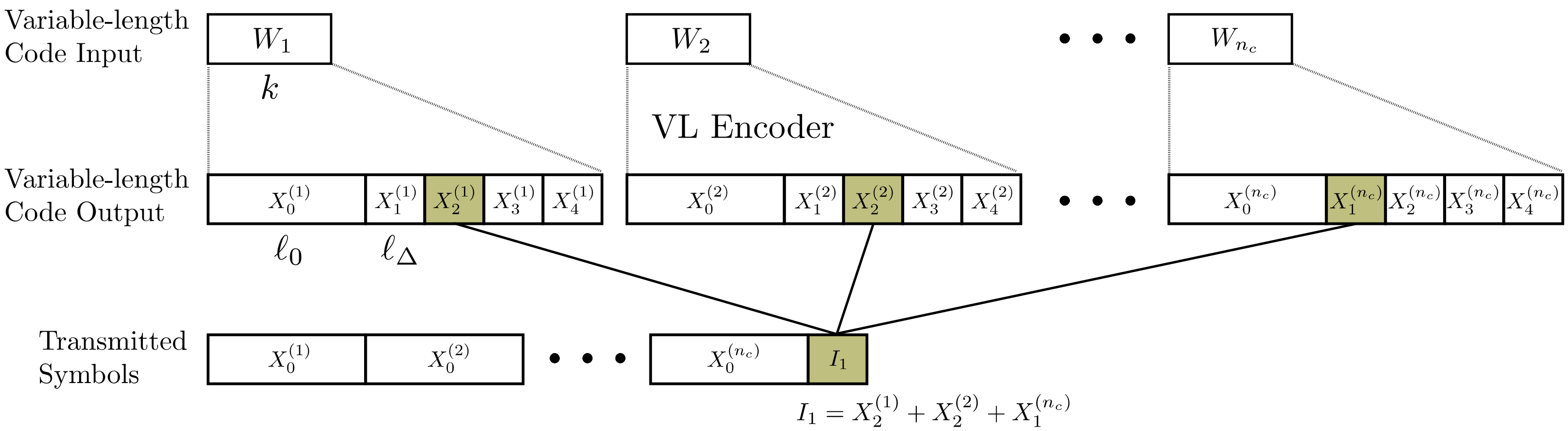

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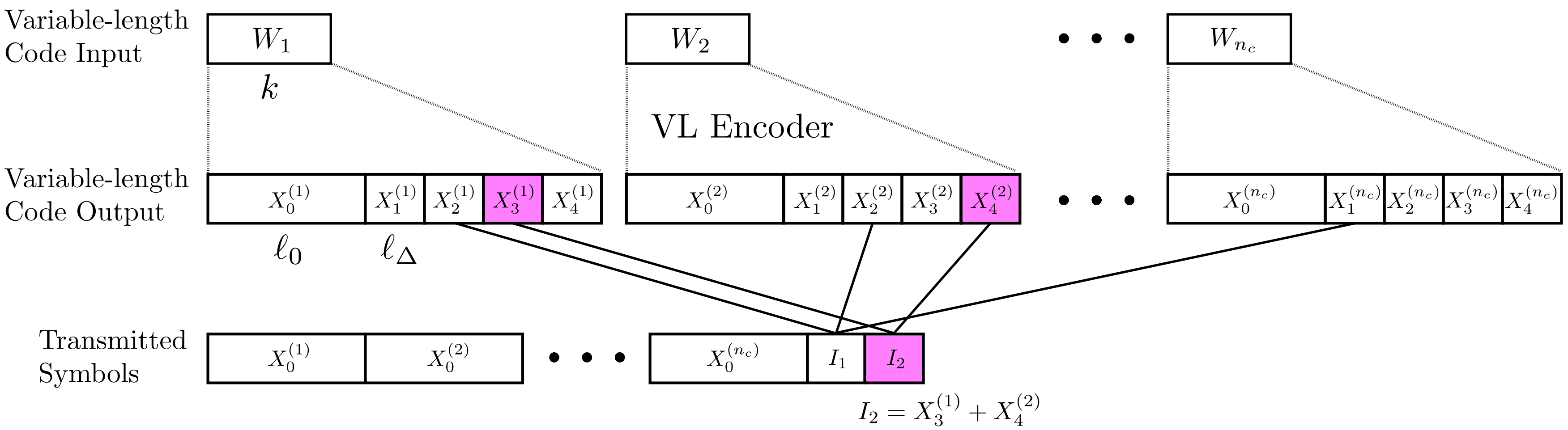

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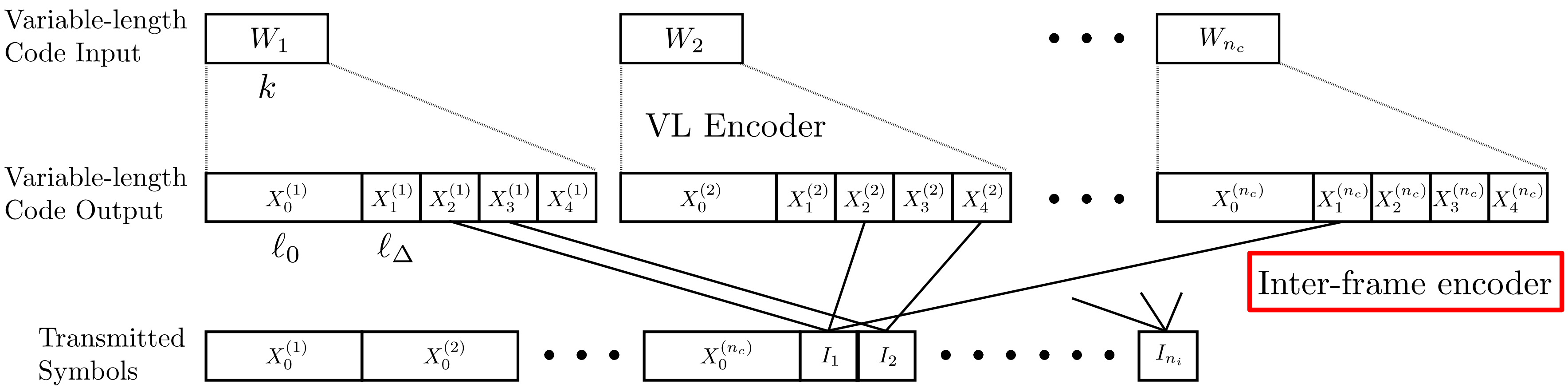
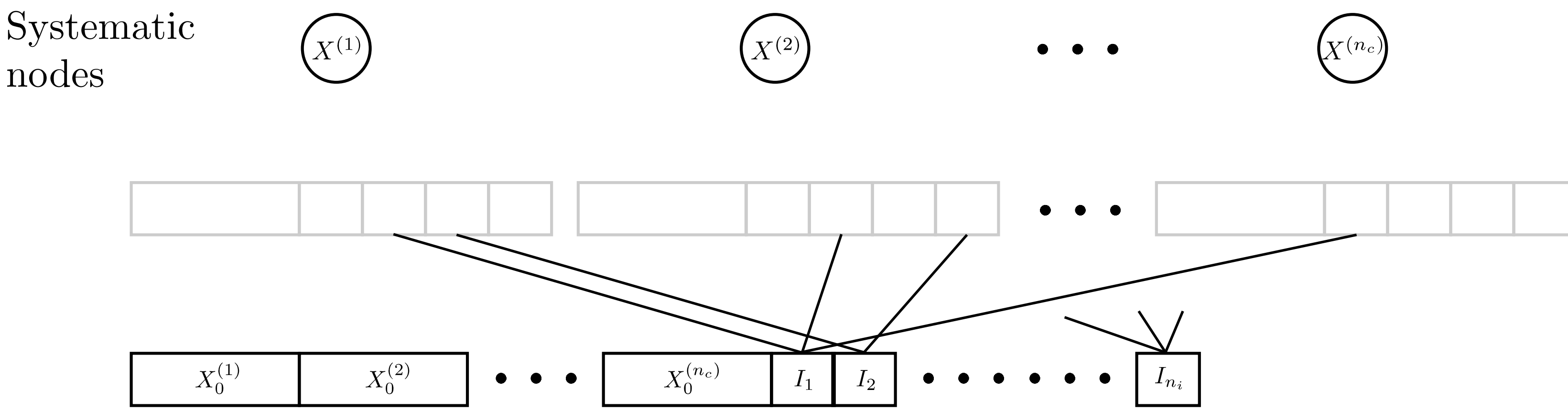


Low Density Generator Matrix (LDGM) [Cheng et al. Allerton 1996] Code



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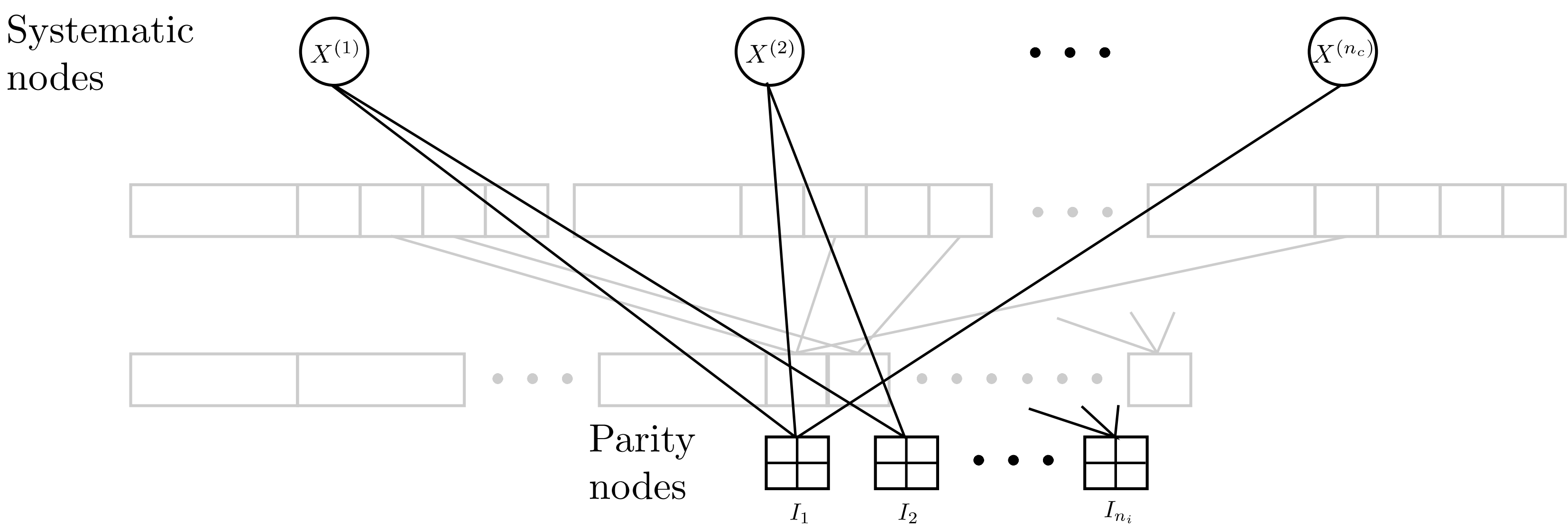

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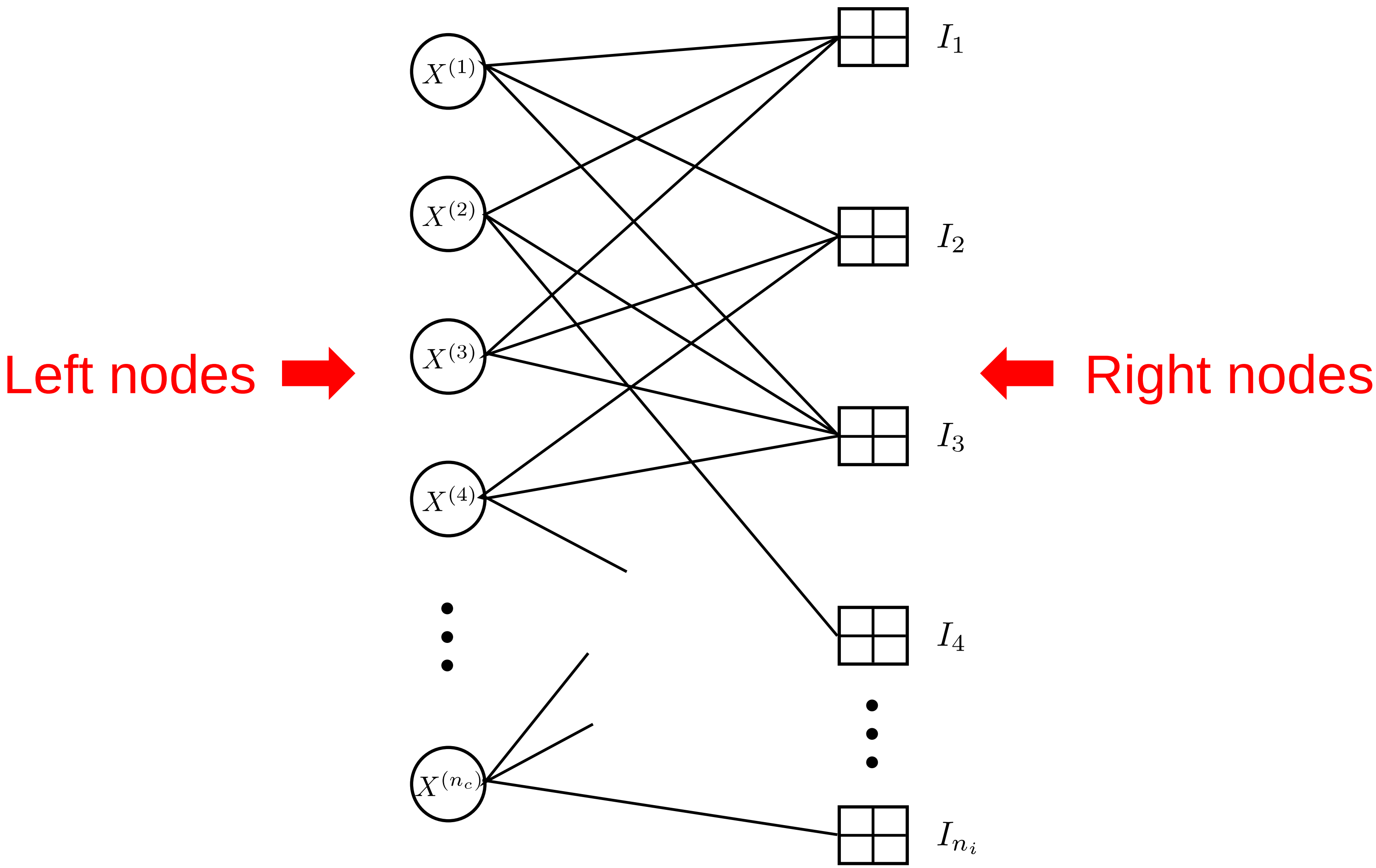
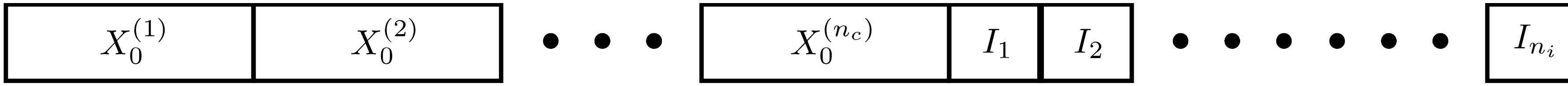
LDGM Code



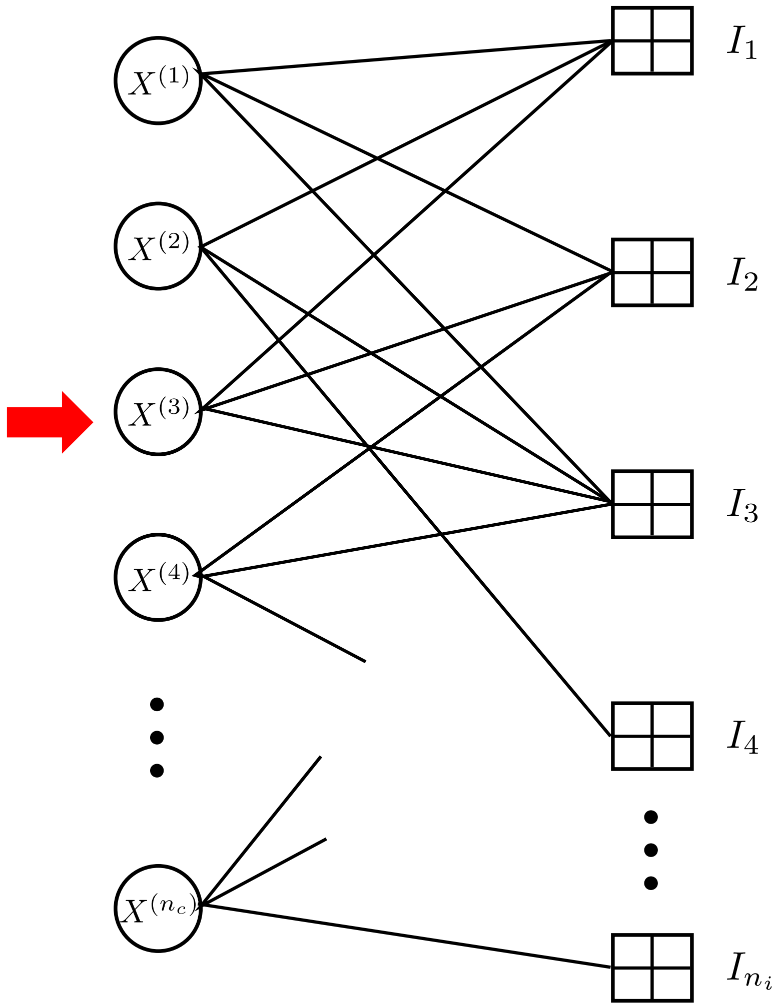
Inter-frame code at the Decoder



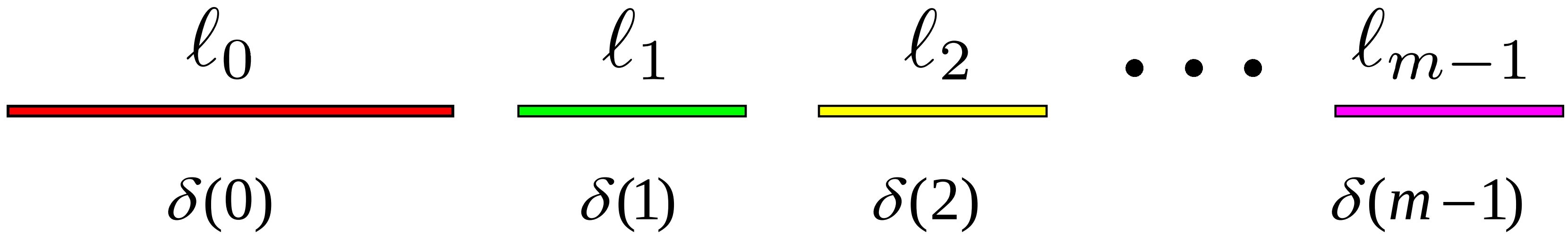
+ Noise

Decoder structure

VL decoders initialized with $X_0^{(i)}$.



Statistics of VL Code in Inter-frame Code Analysis



$$\delta = \{\delta(0), \delta(1), \ldots, \delta(m-1), \delta(m)\}$$

$\delta(n),\ n < m$ is the probability of decoding correctly for the first time after $n+1$ transmissions.

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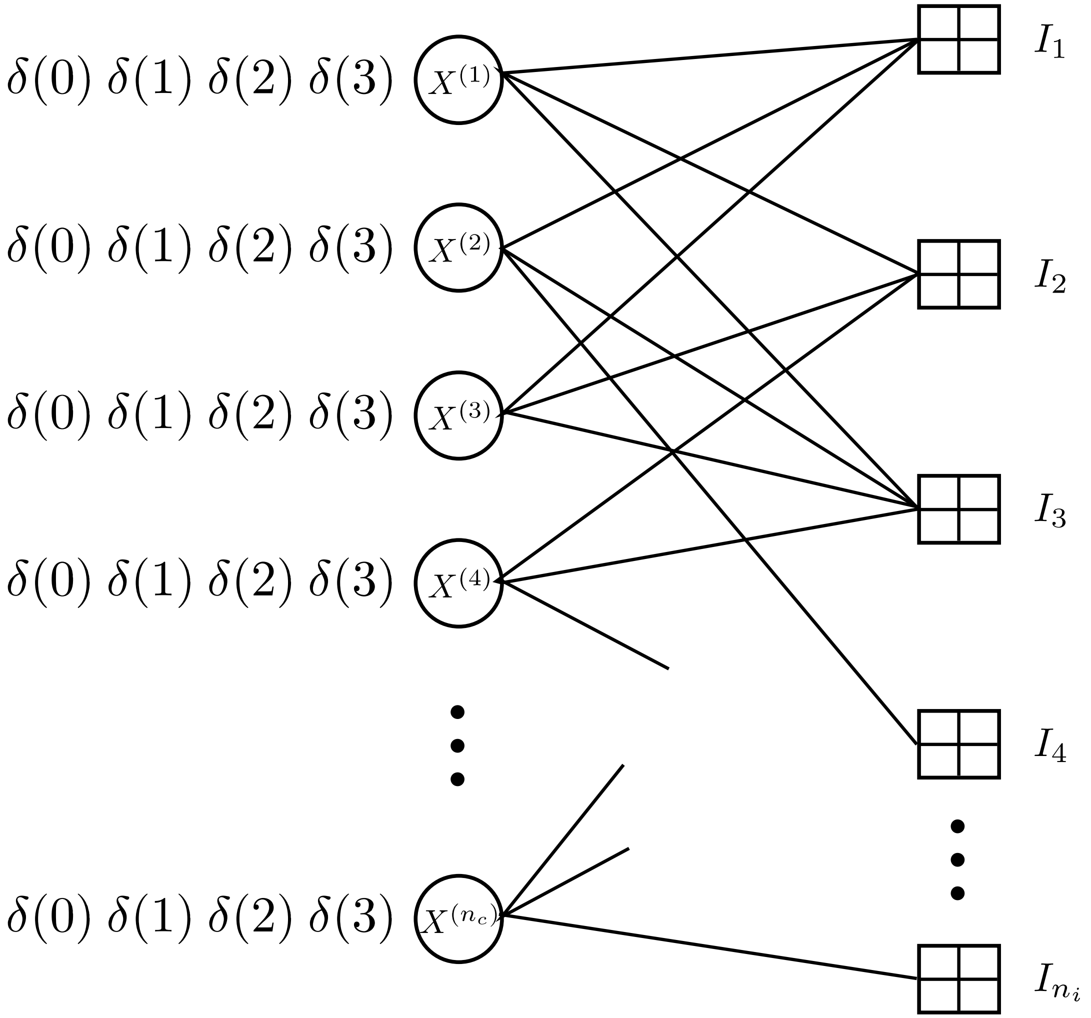
Inter-frame Code – Peeling Decoder

- Every systematic node has a degree of 3 ($m = 3$).

Initialization:

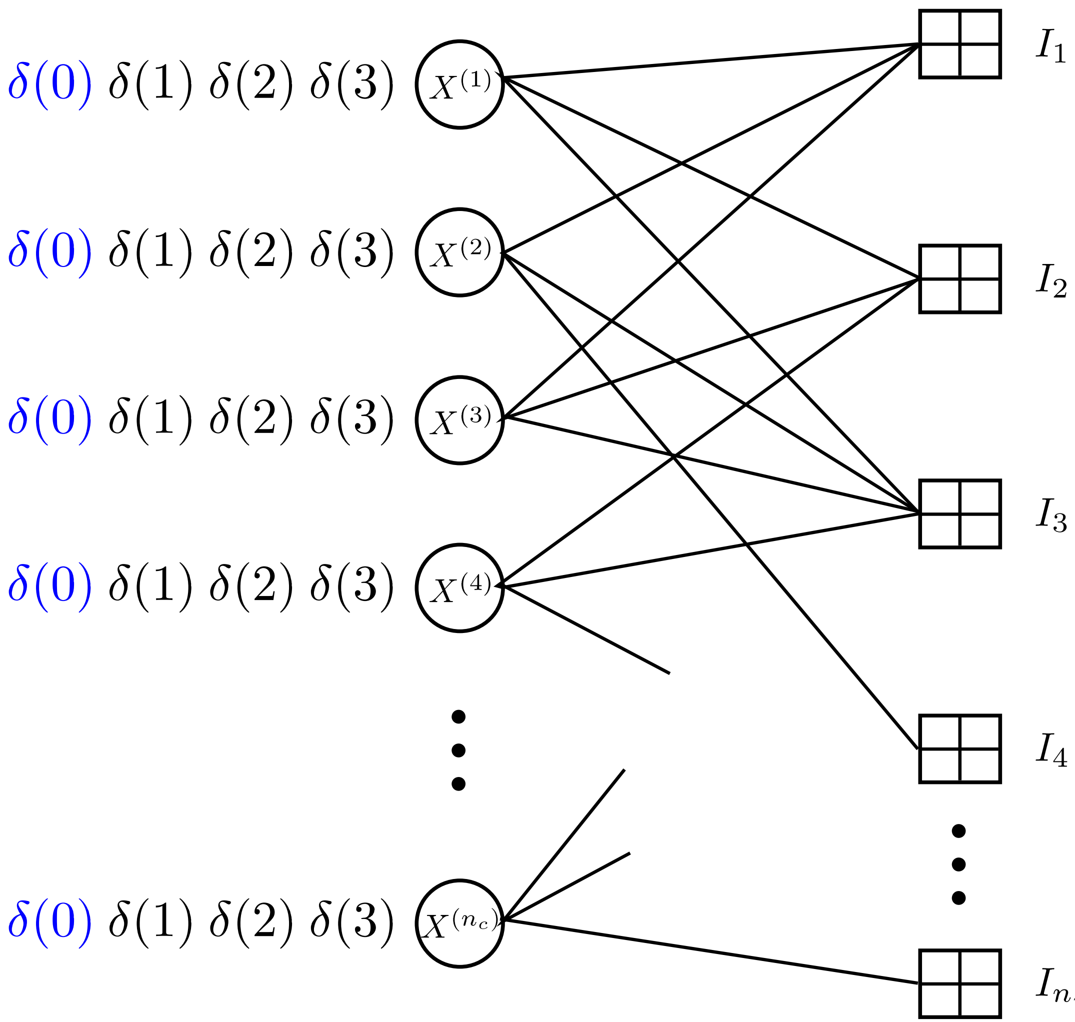
- Every VL decoder observes its noisy highest-rate codeword $X_0^{(i)}$.
- The parity nodes are, likewise, received from the channel.



Inter-frame Code – Peeling Decoder

Iteration 1 (left):

- The systematic nodes (VL decoder) attempt to decode with their highest-rate codewords.
- Each systematic node succeeds with probability $\delta(0)$.



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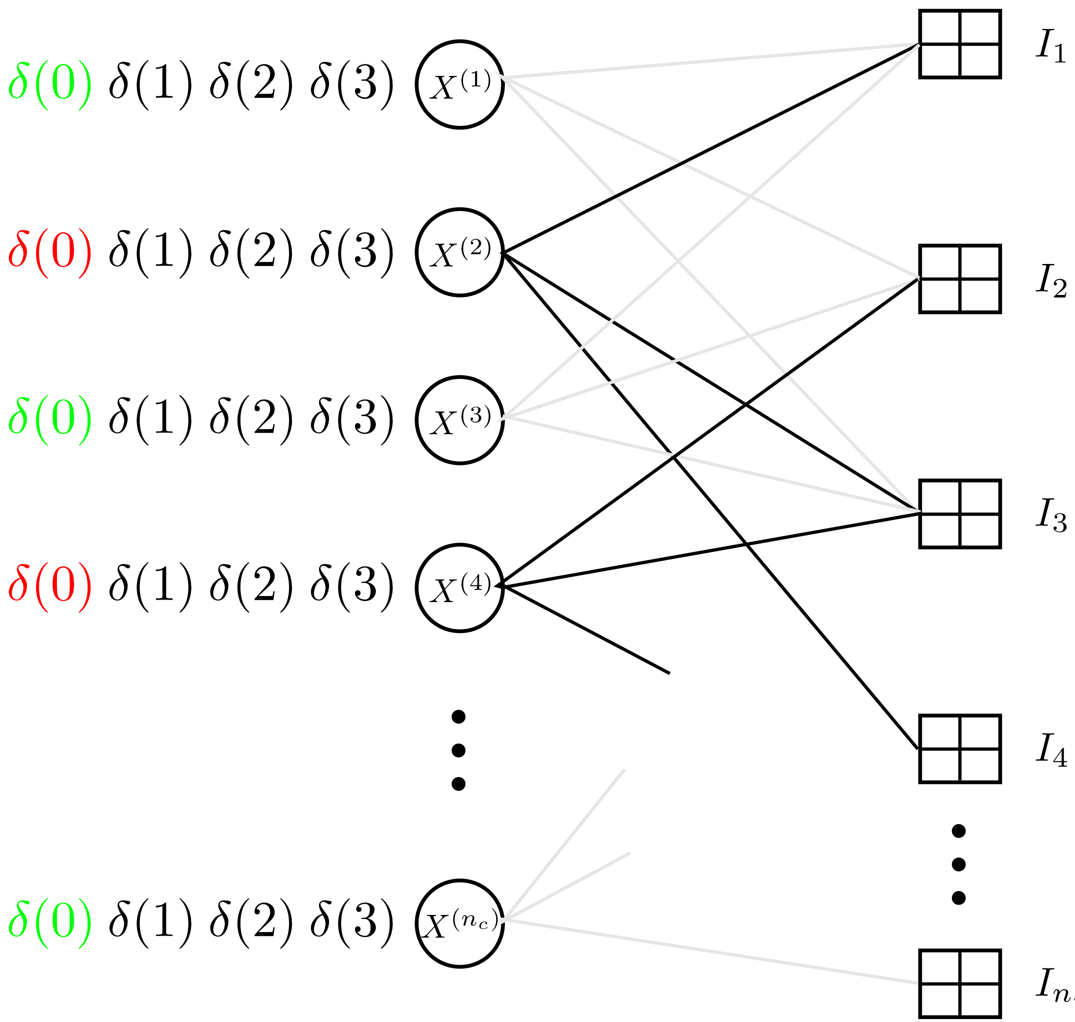
Inter-frame Code – Peeling Decoder

Iteration 1 (left):

- The ones that succeed
  - can compute all their increments.
  - can remove effect of their increments from parities.



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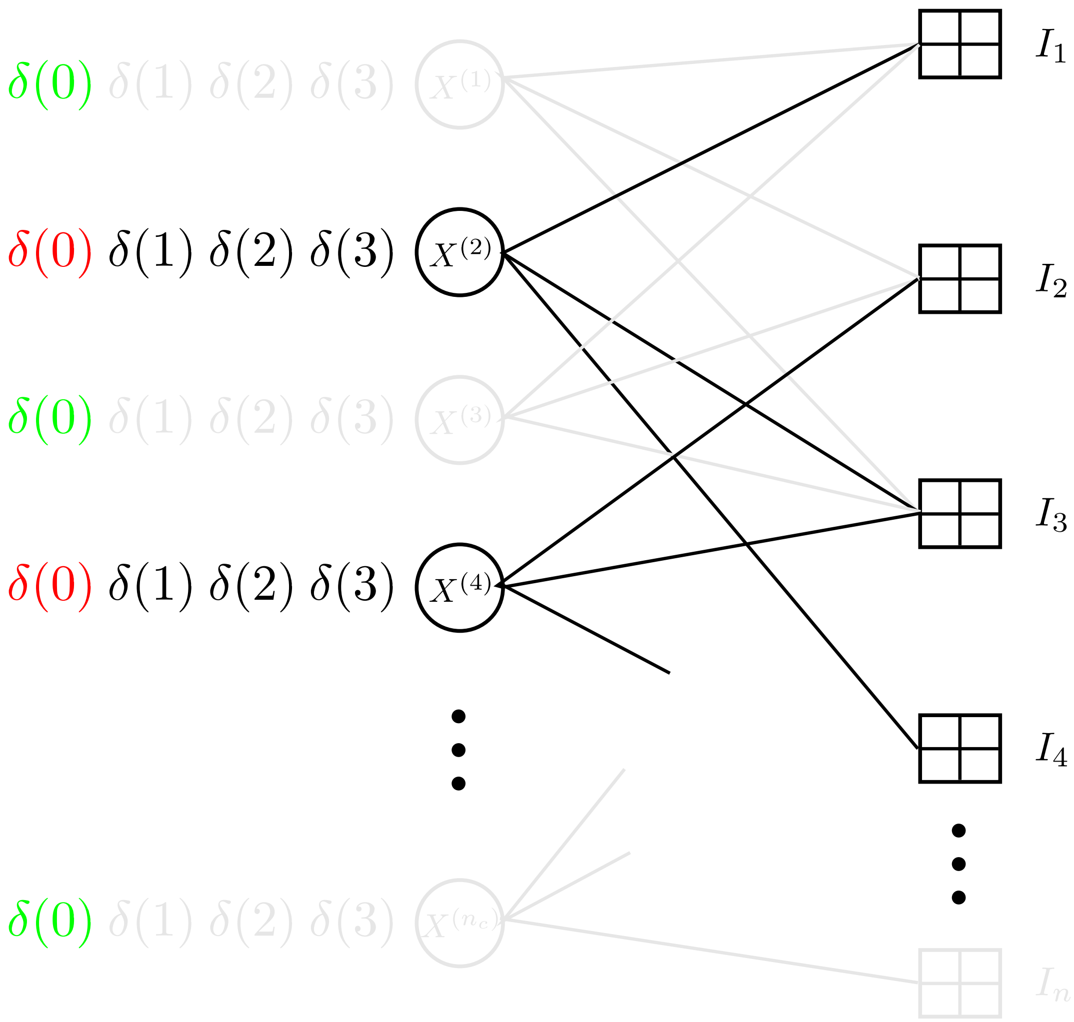

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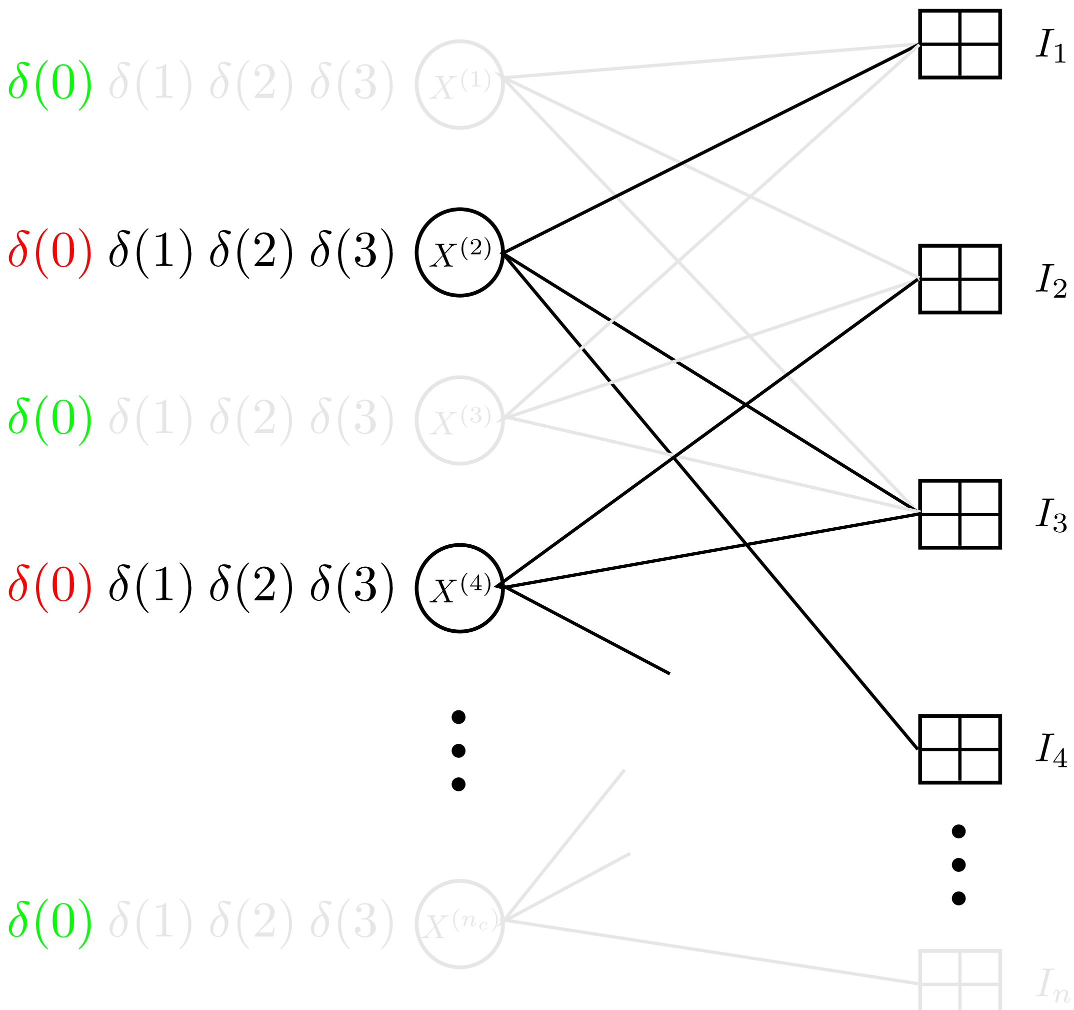
Inter-frame Code – Peeling Decoder

Iteration 1 (left):

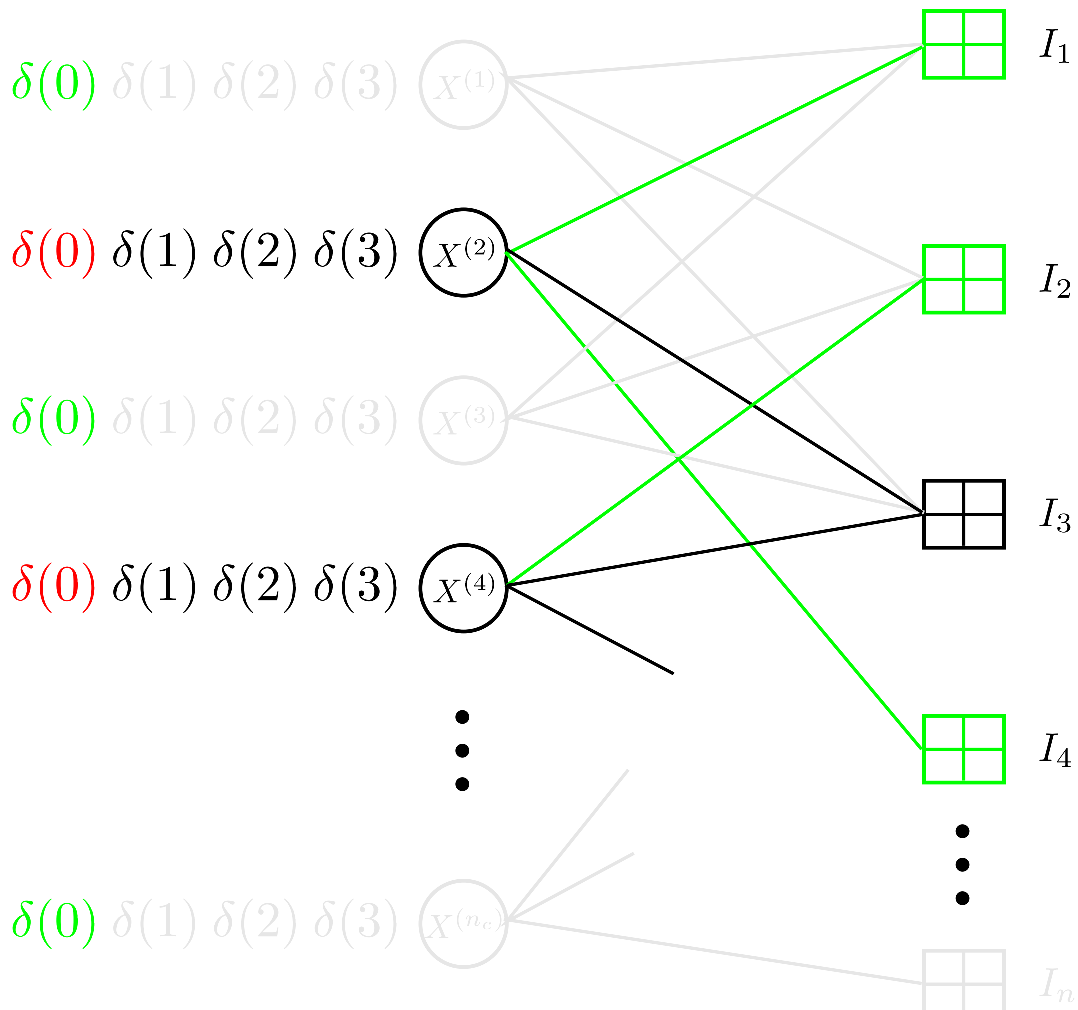
- The ones that fail
  - are retained.
  - when additional increments become available, they can attempt decoding again.



Inter-frame Code – Peeling Decoder

Iteration 1 (right):

- If all but one edge are deactivated, the parity node can become a known increment to a systematic node.



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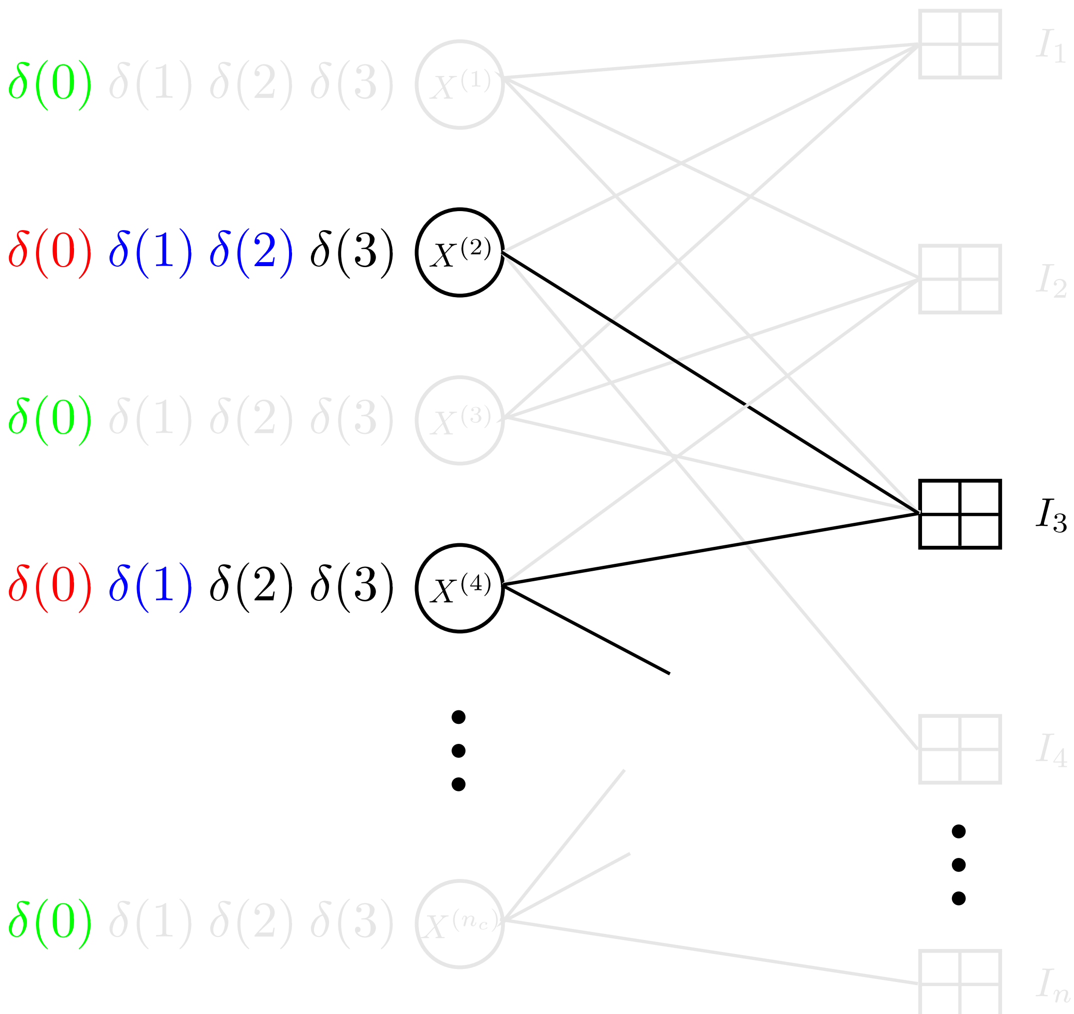
Inter-frame Code – Peeling Decoder

Iteration 1 (right):

- Systematic nodes append available increments to lower their rate.



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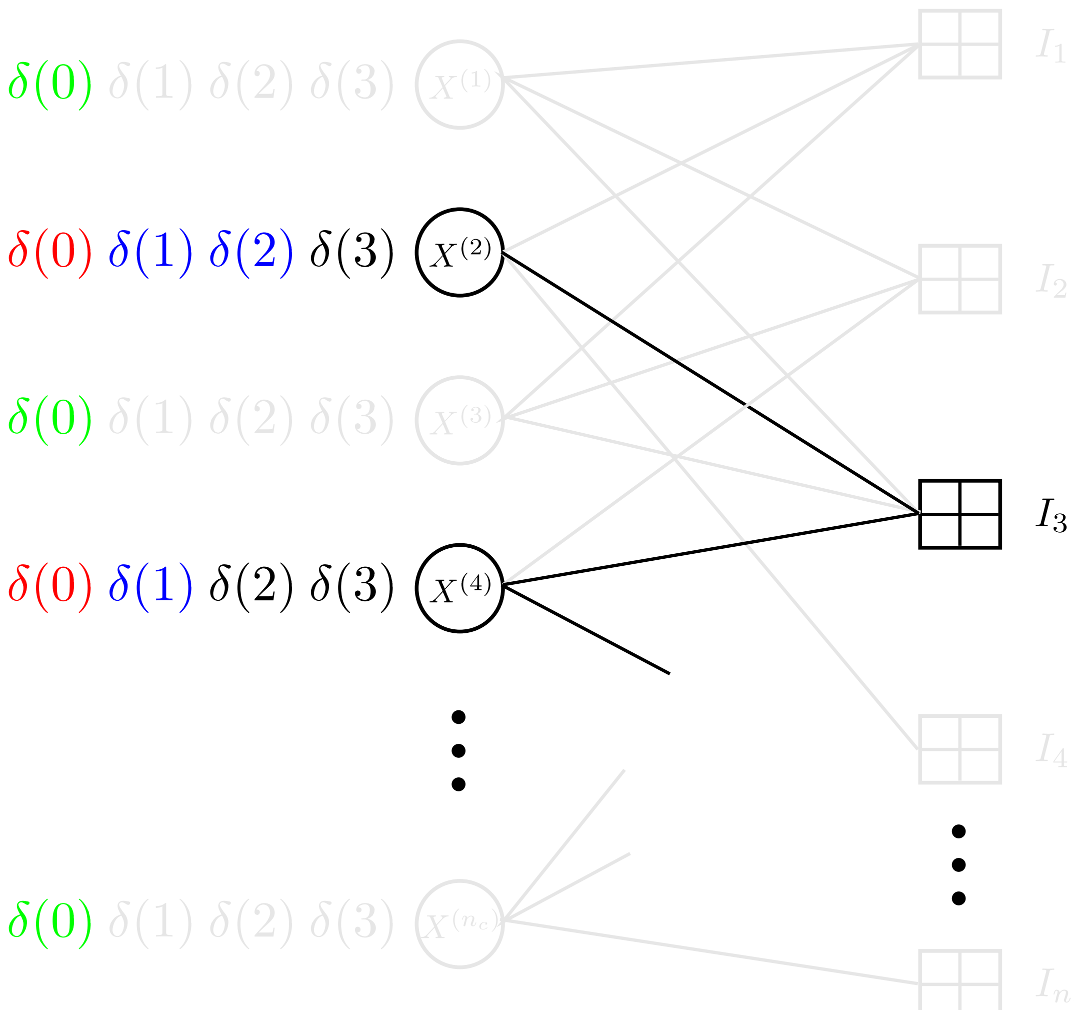
Inter-frame Code – Peeling Decoder

Iteration 2:

- The systematic nodes (yet to decode) decode again if new increments are available to them.



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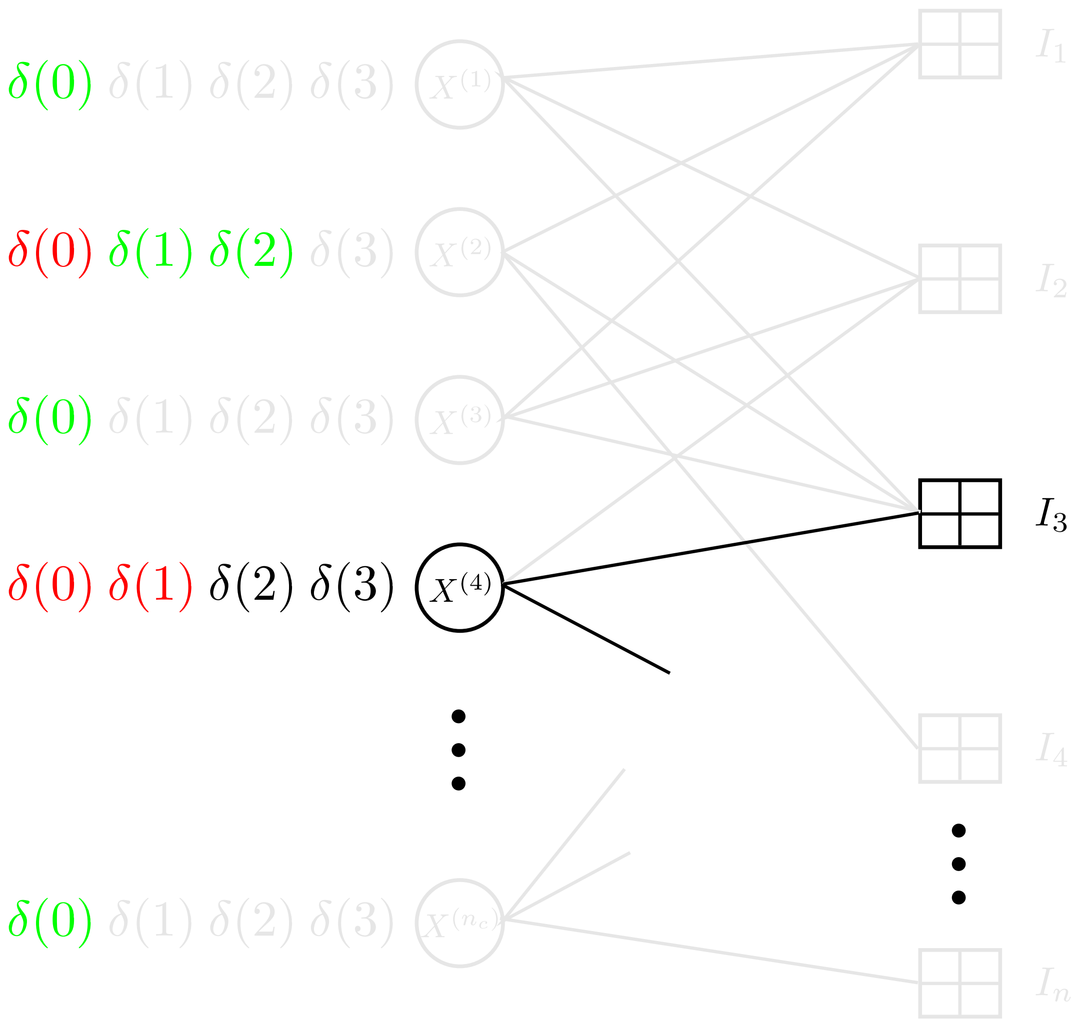
Inter-frame Code – Peeling Decoder

Iteration 2:

- The ones that successfully decode can be removed from the graph along with all their edges.



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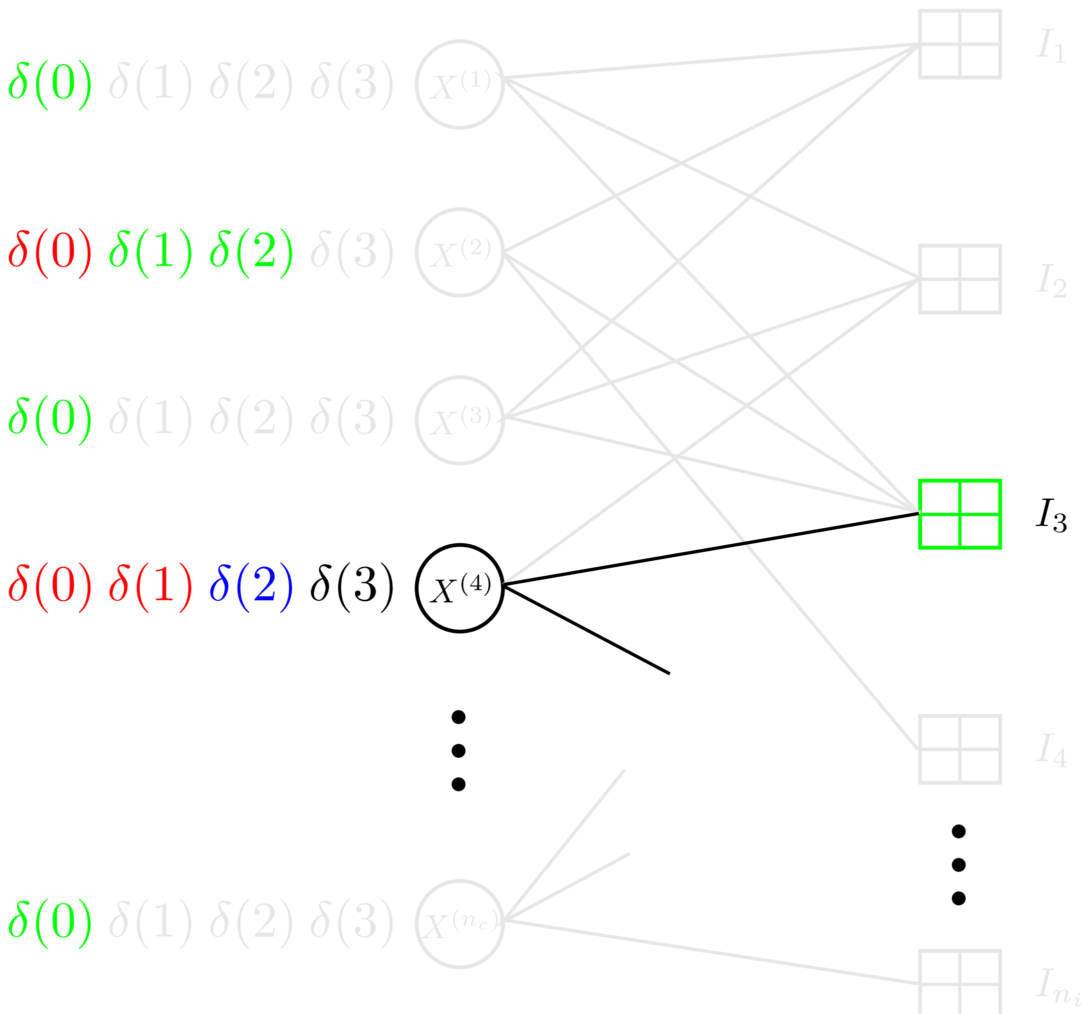
Inter-frame Code – Peeling Decoder

The process continues until no more systematic nodes can be recovered.



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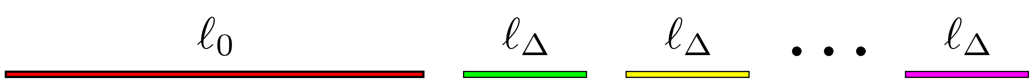
  - Concept
  - Design methods and design examples
    - Differential evolution for degree distribution
    - Quasi-regular heuristic for degree distribution

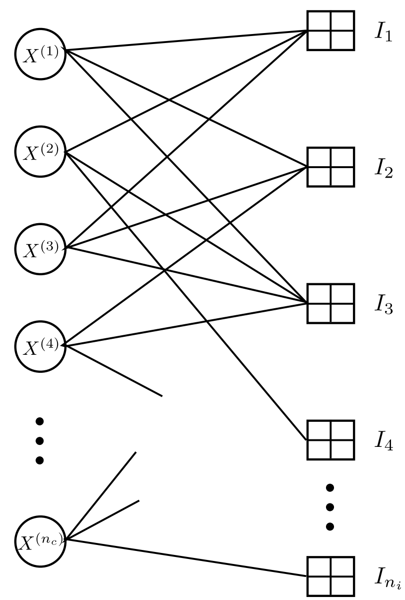
What need to be designed in an inter-frame system?

- Choose a VL code and a maximum number of transmissions ($m = 5$) allowed.

What need to be designed in an inter-frame system?

- Given a VL code with a fixed number of transmissions ($m = 5$) allowed, there are 3 parts to design.
  - The initial transmission length (ℓ_0) and increment length (ℓ_Δ)
  - The degree distributions of the inter-frame code
  - The bipartite graph (parity matrix) of the inter-frame code





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- Given a VL code with a fixed number of transmissions ($m = 5$) allowed, there are 3 parts to design.
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    through brute-force search or sequential differential optimization (SDO) [Vakilinia et al. TCOM 2016]
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    - Differential evolution
    - Quasi-regular heuristics
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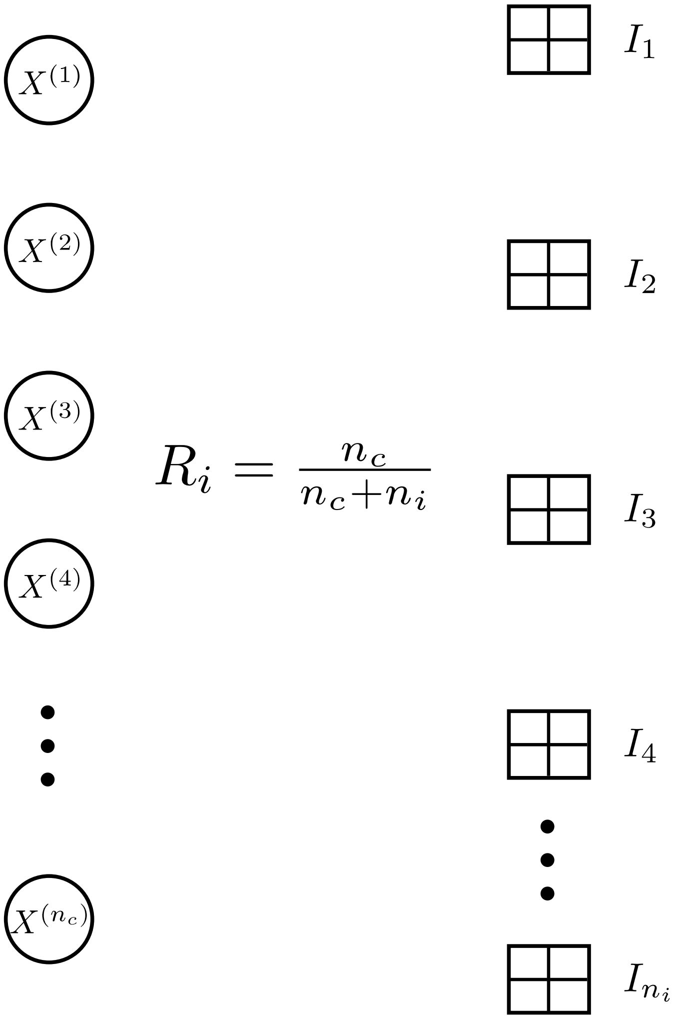
Design Degree Distributions using Differential Evolution

- Given a $\boldsymbol{\delta} = \{\delta(0), \delta(1), \dots, \delta(m)\}$ and m, the objective is to find $\lambda(x), \rho(x)$.
- The peeling decoder can be analyzed using density evolution.
- For a given $\lambda(x), \rho(x)$ pair, density evolution equations can predict the residual systematic-node error rate after a large number of iterations.
- Differential evolution method can then be used to find a $\lambda(x), \rho(x)$ pair with a low-enough failure rate.

Differential Evolution

- Differential evolution is a type of genetic algorithm that optimizes a problem by iteratively improving randomly generated candidates regarding a metric.
- The candidates in our problem are randomly generated $\lambda(x)$,$\rho(x)$ pairs that have a certain LDGM rate R_i.
- The metric is for the codeword (systematic nodes) failure probability ϵ_{FF} to be as small as possible, and below 10^{-3}.
- The LDGM rate R_i is a meta-parameter that are chosen to be as high as the optimization produces valid results.

Inter-frame Code – Rate of LDGM Code



$$R_i = \frac{n_c}{n_c + n_i}$$

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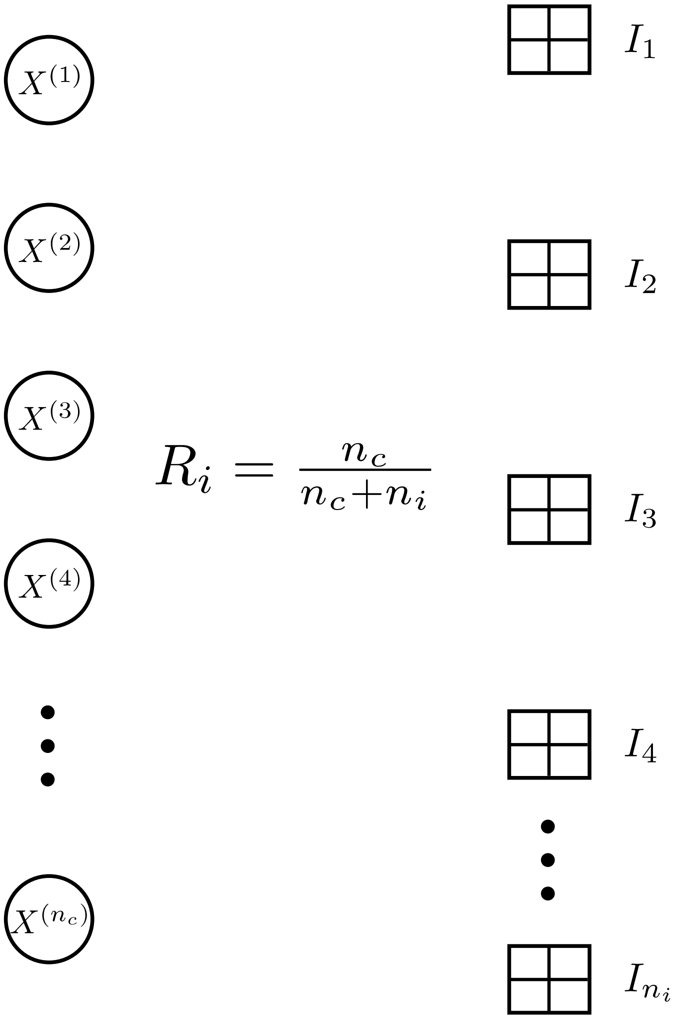
Inter-frame Code – Throughput Rate

$$R_t^{(FF)} = \frac{n_c k(1-\epsilon_{FF})}{n_c \ell_0 + n_i \ell_\Delta}$$

$$R_t^{(FF)} = \frac{k(1-\epsilon_{FF})}{\ell_0 + (R_i^{-1}-1)\ell_\Delta}$$



$$R_i = \frac{n_c}{n_c + n_i}$$

Predict the Failure Probability of the Peeling Decoder

- For a pair of $\lambda(x), \rho(x)$, the codeword failure rate ϵ_{FF} can be calculated using density evolution directly.
- An analytical characterization of ϵ_{FF} can also be used in differential evolution.
- Luby et al. proposed using differential equations or the and-or tree approach to analyze the decoding process of the peeling decoder.
- We extend Luby et al.'s analysis to the inter-frame code by using direct probabilistic arguments.

Peeling Algorithm for Decoder Analysis

- Initially, each VL decoder is assigned a generalized erasure state drawn according to PMF $\boldsymbol{\delta}$.
- Remove all the left nodes that decode, and their incident edges.
- **WHILE** right-degree-one edges (i.e. available increments) remain in the graph
  - Randomly select **one** right-degree-one edge Q_t.
  - Remove Q_t (and its incident right node).
  - Reduce the generalized erasure state of its incident left node by 1.
  - **IF** the left node can decode (the generalized erasure state is 0)
    - Remove the left node and its remaining incident edges.
  - **ENDIF**
- **ENDWHILE**

Characterize the Peeling Process

- As long as there is an edge connects to a degree-1 right node, the peeling process continues.
- Peeling process metric $r_1(x)$: the probability that a randomly picked edge in the initial bipartite graph has not been removed after t iterations, and connects to a degree-1 right node.
- We use $r_1(x)$ to predict ϵ_{FF}.

Definition of x

- Define $x(t)$ or simply x as the probability that a randomly selected edge in the initial graph that is not in the set $\{Q_1, \ldots, Q_t\}$.
- In [Luby et al. IT 2001], x is defined with a differential equation to solve differential equations to find $r_1(x)$.

Characterize the Peeling Process

- $p_l(x)$: the probability that a randomly selected edge in the initial graph has as its incident left node a VL decoder that cannot decode after $\{Q_1, \ldots, Q_t\}$ have been provided as potential increments by all the other edges connecting to that VL decoder.
- $p_r(x)$: the probability that a randomly selected edge in the initial graph has as its incident right node a node with exactly one edge remaining after $\{Q_1, \ldots, Q_t\}$ have been provided as increments to the VL decoders.

Characterize the Peeling Process

$$r_1(x) = p_l(x)p_r(x) - p_l(x)(1-x)$$

$$p_l(x) = \sum_{\omega=1}^{m} \delta(\omega) \sum_{i=1}^{d_L} \lambda_i \sum_{j=0}^{\min(\omega,i)-1} \binom{i-1}{j} (1-x)^j x^{i-1-j}$$

$$p_r(x) = \rho(1 - p_l(x))$$

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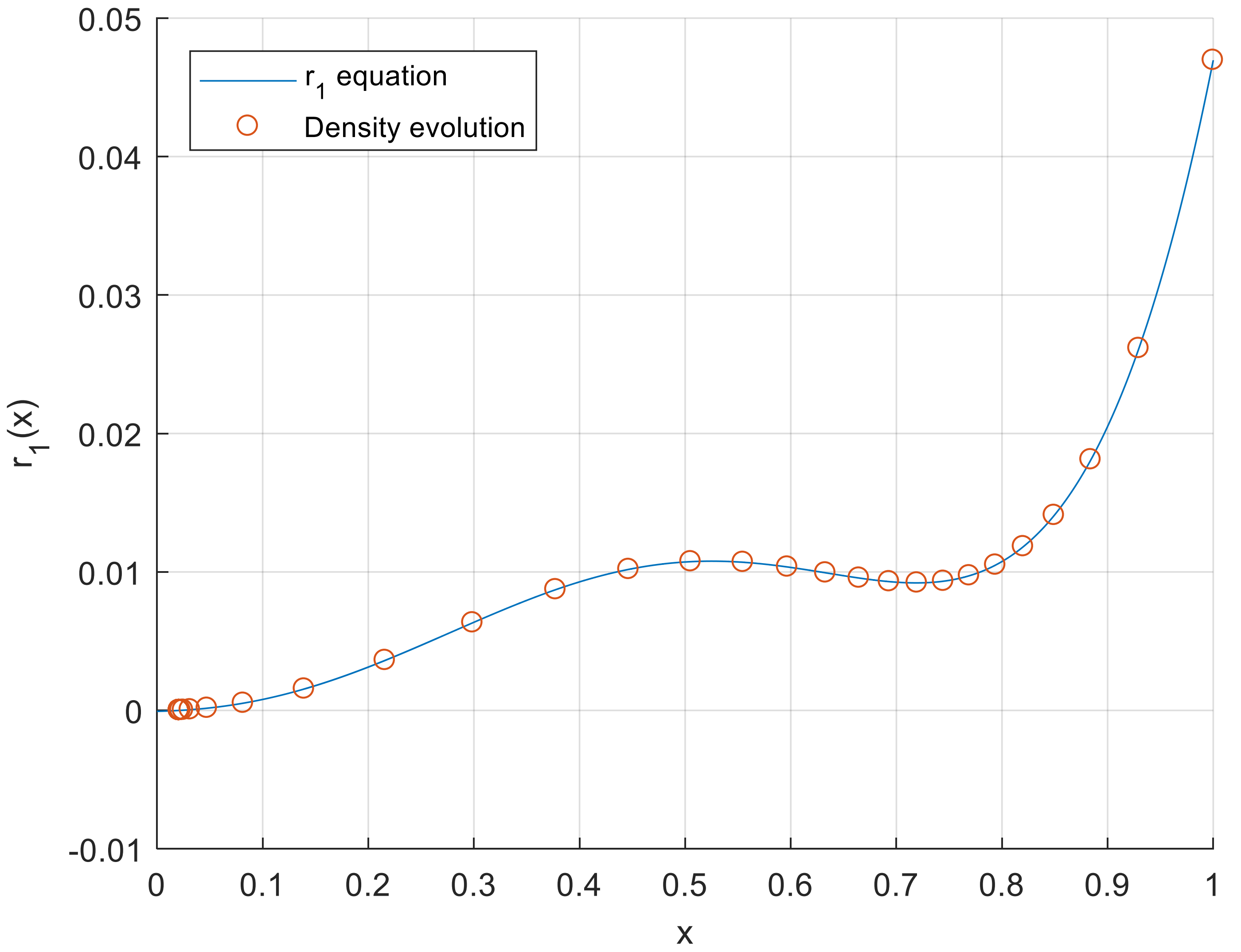
Characterize the Peeling Process



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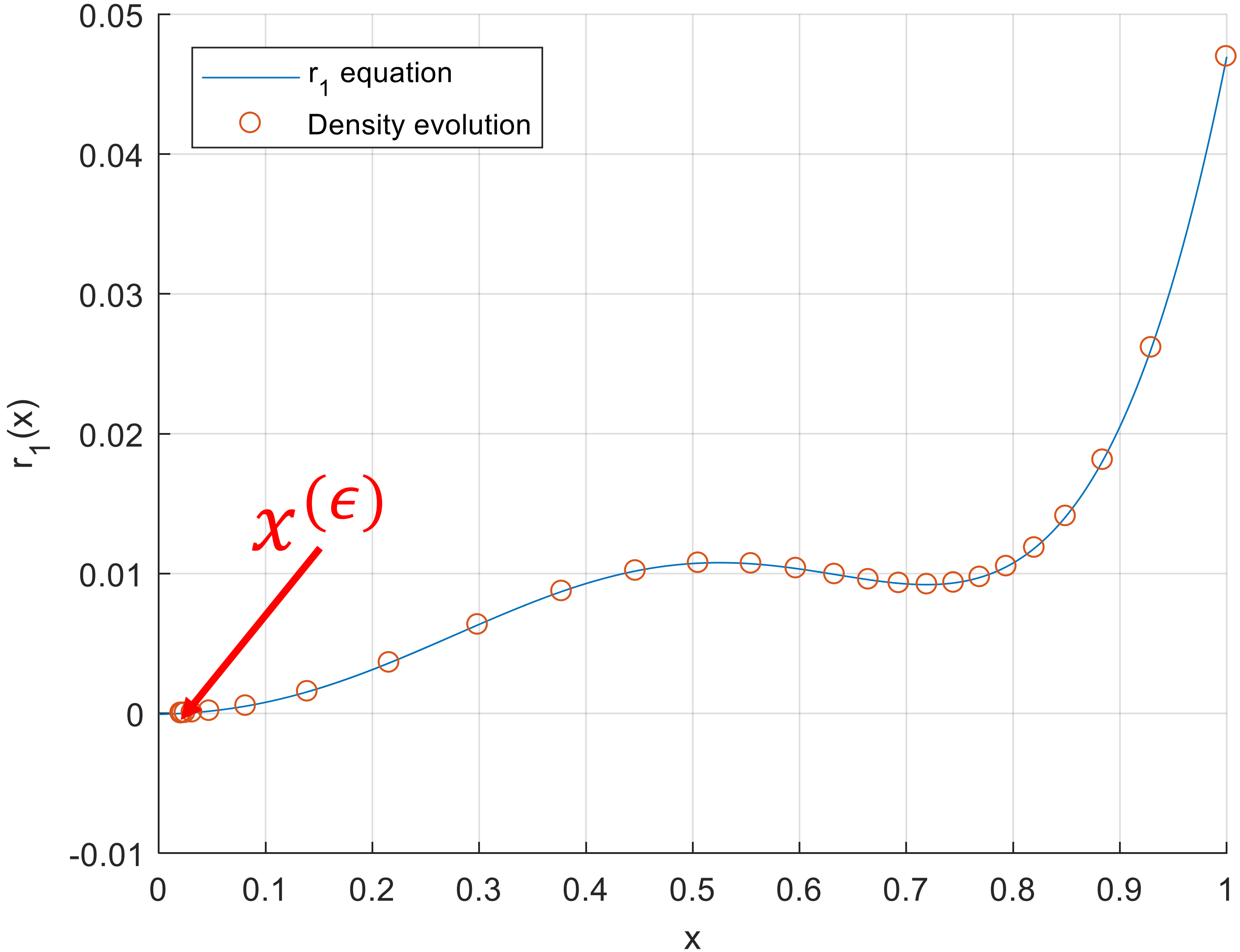

Probability of Failure ϵ_{FF}

$$\epsilon_{FF} = \sum_{\omega=1}^{m} \delta(\omega) \sum_{i=1}^{d_L} \Lambda_i \sum_{j=0}^{\min(\omega-1,i)} \binom{i}{j} \left(1 - x^{(\epsilon)}\right)^j \left(x^{(\epsilon)}\right)^{i-j}$$

$$\Lambda_i = \frac{\lambda_i / i}{\sum_{j=1}^{d_L} \lambda_i / i}$$

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Convolutional Code as VL Code [Williamson et al. TCOM 2014]

VL encoder

k=64 bits, Rate-1/3, 1024-state, tail-biting convolutional code (TBCC) with pseudorandom puncturing [Ma et al. TCOM 1986]

Channel

Binary-input AWGN Channel with SNR=2 dB

VL decoder

Tail-biting reliability-output Viterbi algorithm (ROVA) [Raghavan et al. TIT 1998]

Convolutional VL Code parameters with Constant-size Increments

$\boldsymbol{\ell_0}$	**$\boldsymbol{\ell_\Delta}$ for $\boldsymbol{m = 5}$ (four increments)**	**Throughput Rate $R_t^{(FB)}$ with ACK/NACK Feedback**	**Percentage of Capacity of 2dB BI-AWGN**
108 bits	16 bits	0.5208	81.10%

- $\boldsymbol{\delta} = \{0.333, 0.449, 0.182, 0.0316, 0.00402, 0.000505\}$

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Design Example – Regular LDGM Code

- Systematic node degree: 4
- Parity node degree: 3
- LDGM code design rate $R_i = 0.4286$
- Number of systematic nodes = 100,000

Throughput Rate $R_t^{(FB)}$ with ACK/NACK Feedback	**Throughput Rate $R_t^{(FF)}$ - inter-frame code (regular LDGM)**
0.5208	0.4945

Design Example – Irregular LDGM Code

- Maximum systematic node degree: 4
- Maximum parity node degree: 10
- LDGM code design rate $R_i = 0.48$
- Number of systematic nodes = 100,000

Throughput Rate $R_t^{(FB)}$ with ACK/NACK Feedback	**Throughput Rate $R_t^{(FF)}$ - inter-frame code (regular LDGM)**	**Throughput Rate $R_t^{(FF)}$ - inter-frame code (irregular LDGM)**
0.5208	0.4945	0.5102

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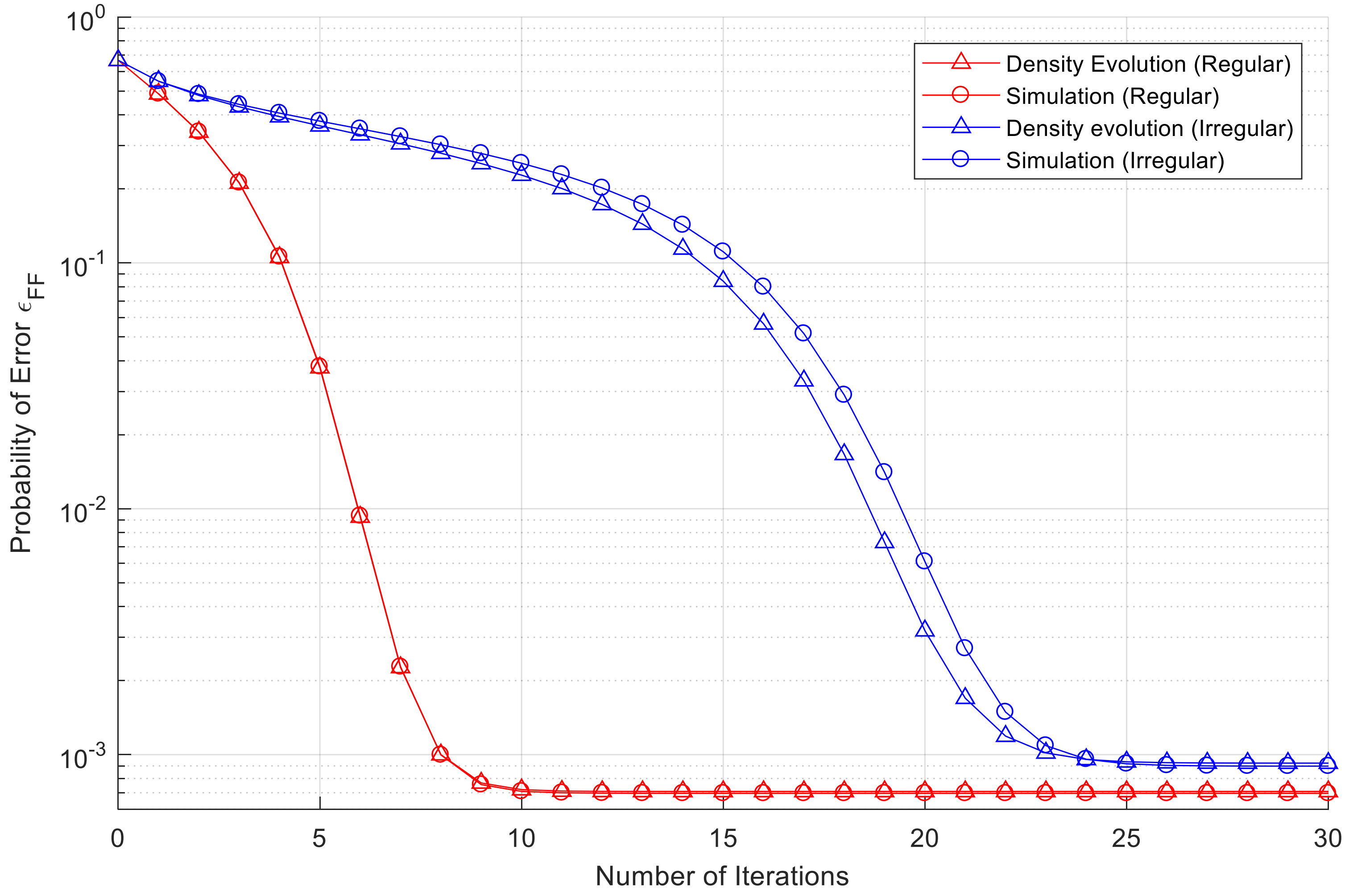
Probability of Error Characterization of the 100,000 Systematic Node Codes



Design Example – Shorter LDGM Code

- Maximum systematic node degree: 4
- Maximum parity node degree: 10
- LDGM code design rate $R_i = 0.46$
- Number of systematic nodes: 1000

Throughput Rate $R_t^{(FB)}$ with ACK/NACK Feedback	Throughput Rate $R_t^{(FF)}$ - inter-frame code (irregular LDGM)
0.5208	0.5044

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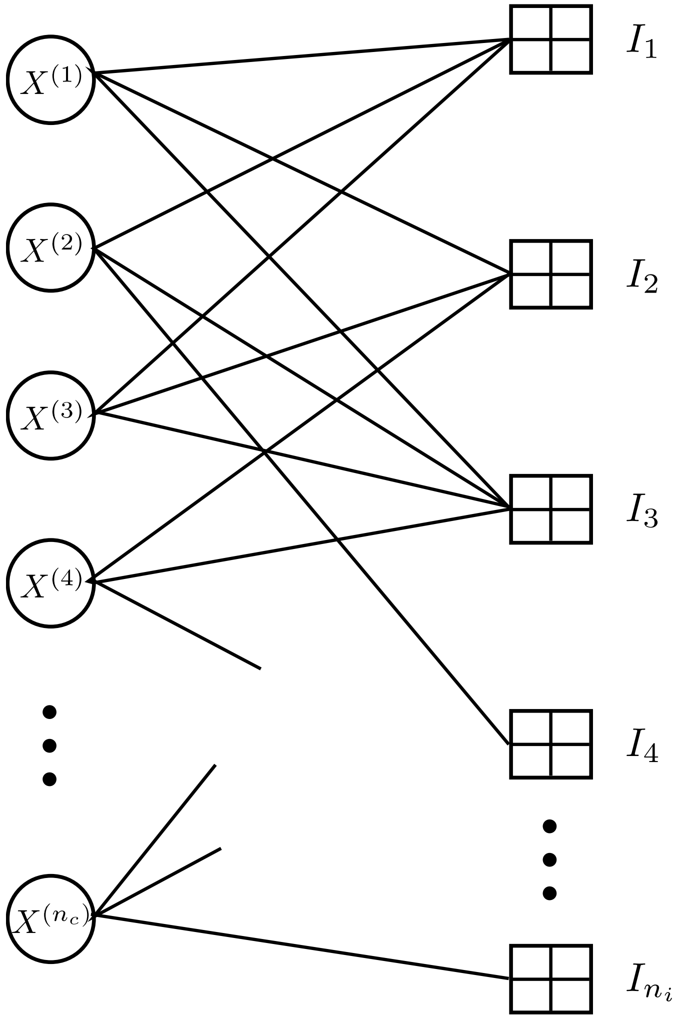
Design Example – Comparison vs Capacity

	VL Code with ACK/NACK Feedback	100,000 systematic nodes		1000 systematic nodes
		Regular LDGM	Irregular LDGM	Irregular LDGM
Throughput rate	0.5208	0.4945	0.5102	0.5044
Percentage of Capacity of 2dB BI-AWGN	81.10%	77.01%	79.45%	78.55%
Percentage of ACK/NACK Feedback Throughput	---	95.0%	98.0%	96.9%

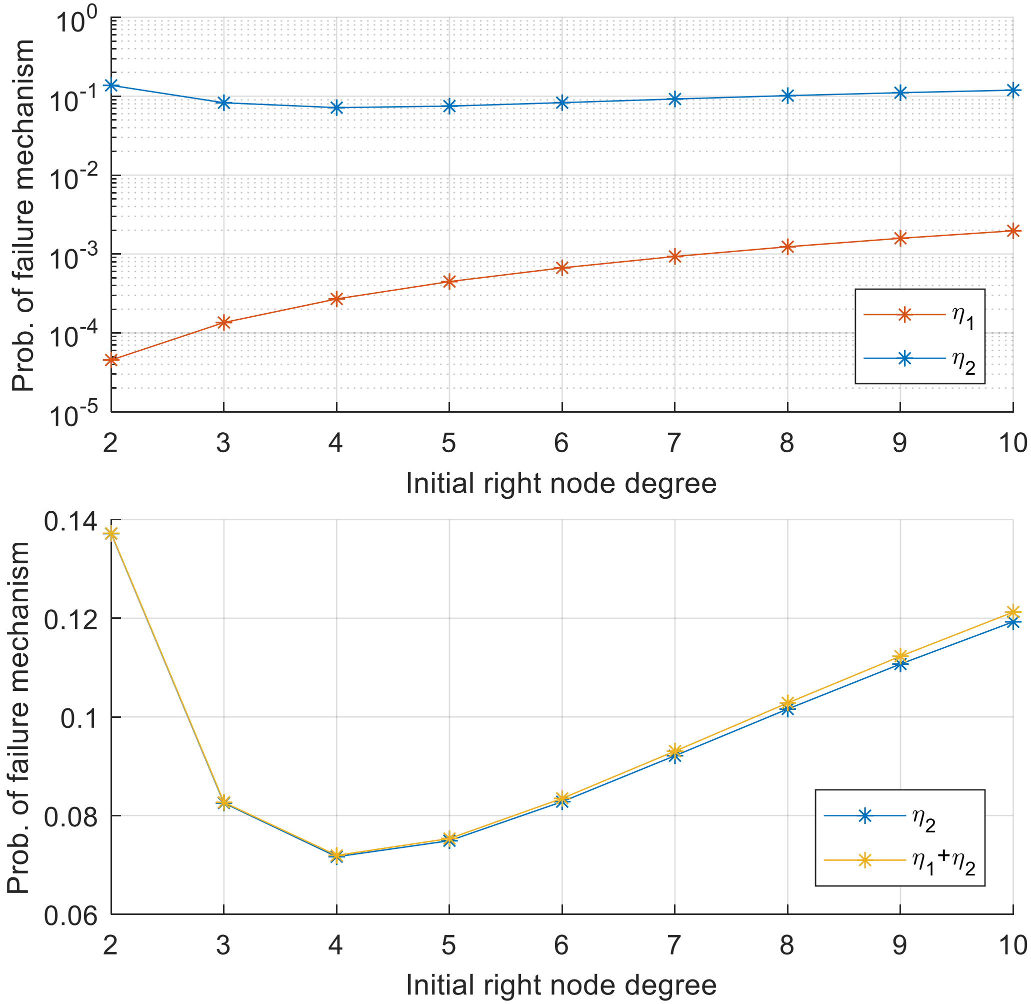
The throughput loss is the result of using more linear combinations of increments (right nodes) than the feedback system.

Three Mechanisms of Throughput Loss

- The degree of the right node of interest (RNOI) never decreases below two. (η_1)
- The degree of the RNOI decreases from two or more to zero in a single iteration of the peeling decoder so that it never provides an increment. (η_2)
- The degree of the RNOI achieves the value of one during an iteration so that it provides an increment to a left node, but other right nodes simultaneously provide the remaining required increments to that left node making the RNOI's increment superfluous. (η_3)



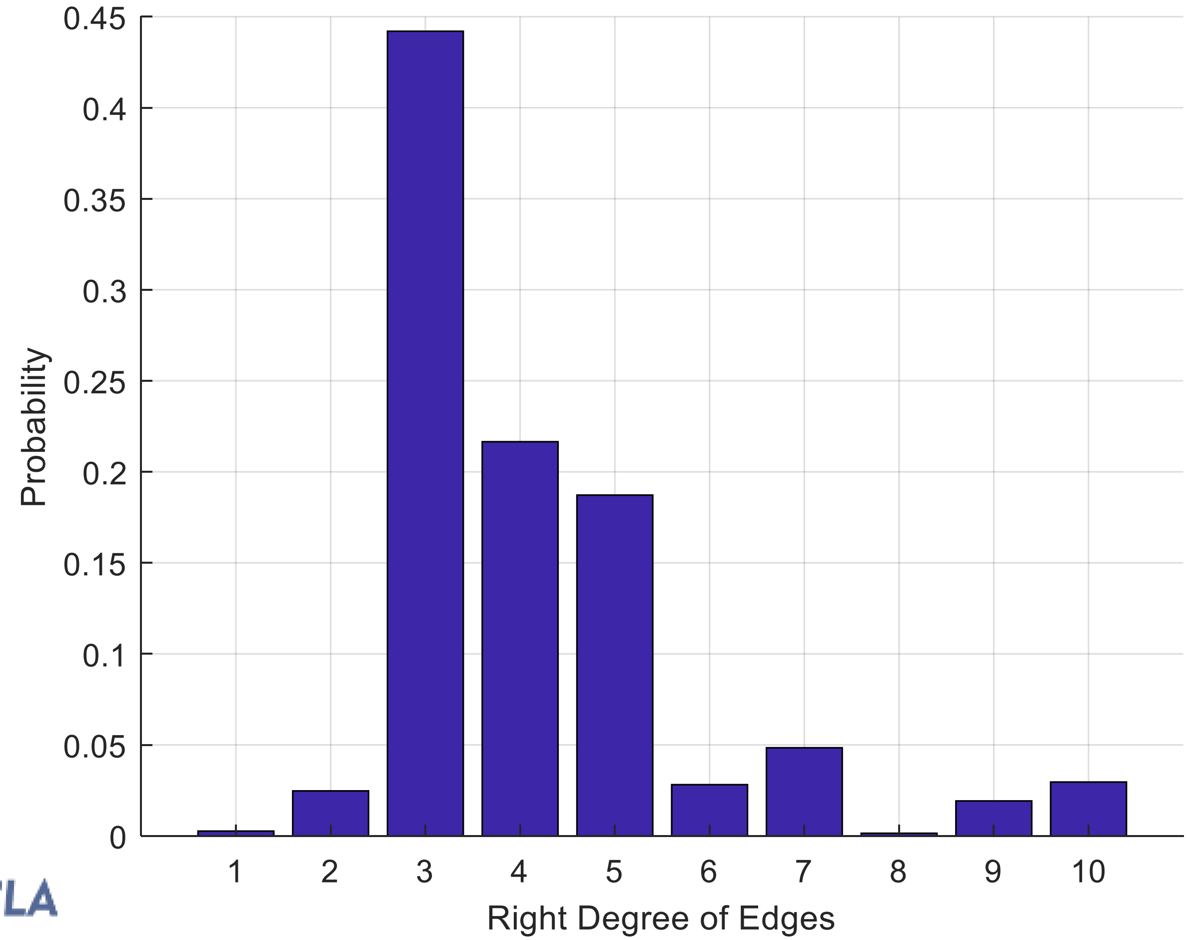
Probability of Failure Mechanisms



Quasi-regular heuristic for the right degree distribution

Right Degree Distribution Example from Differential Evolution

- The right degree distribution of the 100,000-systematic-node irregular LDGM code is:



Quasi-regular!

This is different from the Poisson right degree distribution proposed in [Luby et al. IT 2001] and Zeineddine et al. JSAC 2016] .

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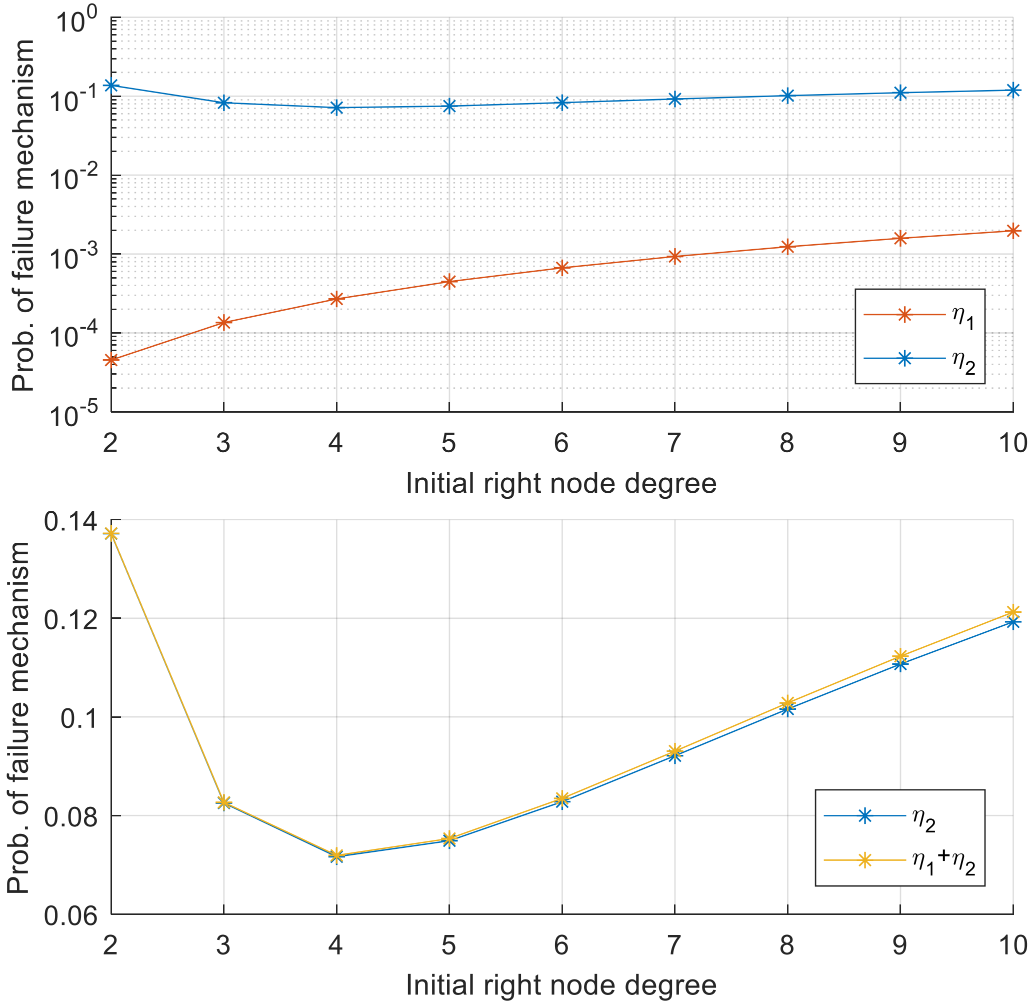
Outline

- **Previous work**: Approaching Capacity with Short Blocklengths using Incremental Redundancy and ACK/NACK Feedback
- **New Idea**: Approaching Capacity using many Short-blocklength Codes with Incremental Redundancy in Parallel *Without Feedback*
  - Concept
  - Design methods and design examples
    - Differential evolution for degree distribution
    - Quasi-regular heuristic for degree distribution

Quasi-regular heuristic for degree distribution

- Given a $\boldsymbol{\delta} = \{\delta(0), \delta(1), \ldots, \delta(m)\}$ and m, the objective is to find $\lambda(x), \rho(x)$.
- Set $\lambda(x) = x^3$ for $m = 5$ so that each left node has the maximum capacity of receiving required increments.
- Select $\rho(x) = \alpha x^2 + (1 - \alpha)x^3$ for example where α is the design parameter.
- Find α that maximizes the throughput and guarantees the target failure probability.

Which adjacent degrees to choose?



From a $\lambda(x), \rho(x)$ pair generated by differential evolution.

Which adjacent degrees to choose?

- For the VL code with feedback, define β_{FB} as the expected number of increments required by a VL decoder.

$$\beta_{FB} = \sum_{i=1}^{m-1} i\delta(i) + (m-1)\delta(m) = \mathbb{E}(\boldsymbol{\delta}) - \delta(m)$$

- For an inter-frame code, define β_{FF} as the average number of combined increments per left node. $\beta_{FF} = R_i^{-1} - 1.$

- Lower bound on β_{FF}:

$$\beta_{FF} \geq \beta_{FB}$$

Which adjacent degrees to choose?

- When the left degree distribution is regular, $\lambda(x) = x^{m-1}$, define a_R as the average right node degree.

$$\beta_{FF} = \frac{\int_0^1 \rho(x)\, dx}{\int_0^1 \lambda(x)\, dx} = \frac{m-1}{a_R}$$

$$\beta_{FF} \geq \beta_{FB} \Rightarrow a_R \leq \frac{m-1}{\beta_{FB}}$$

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Which adjacent degrees to choose?

- For the convolutional code example, $\beta_{FB} = 0.9260$, $m = 5$.

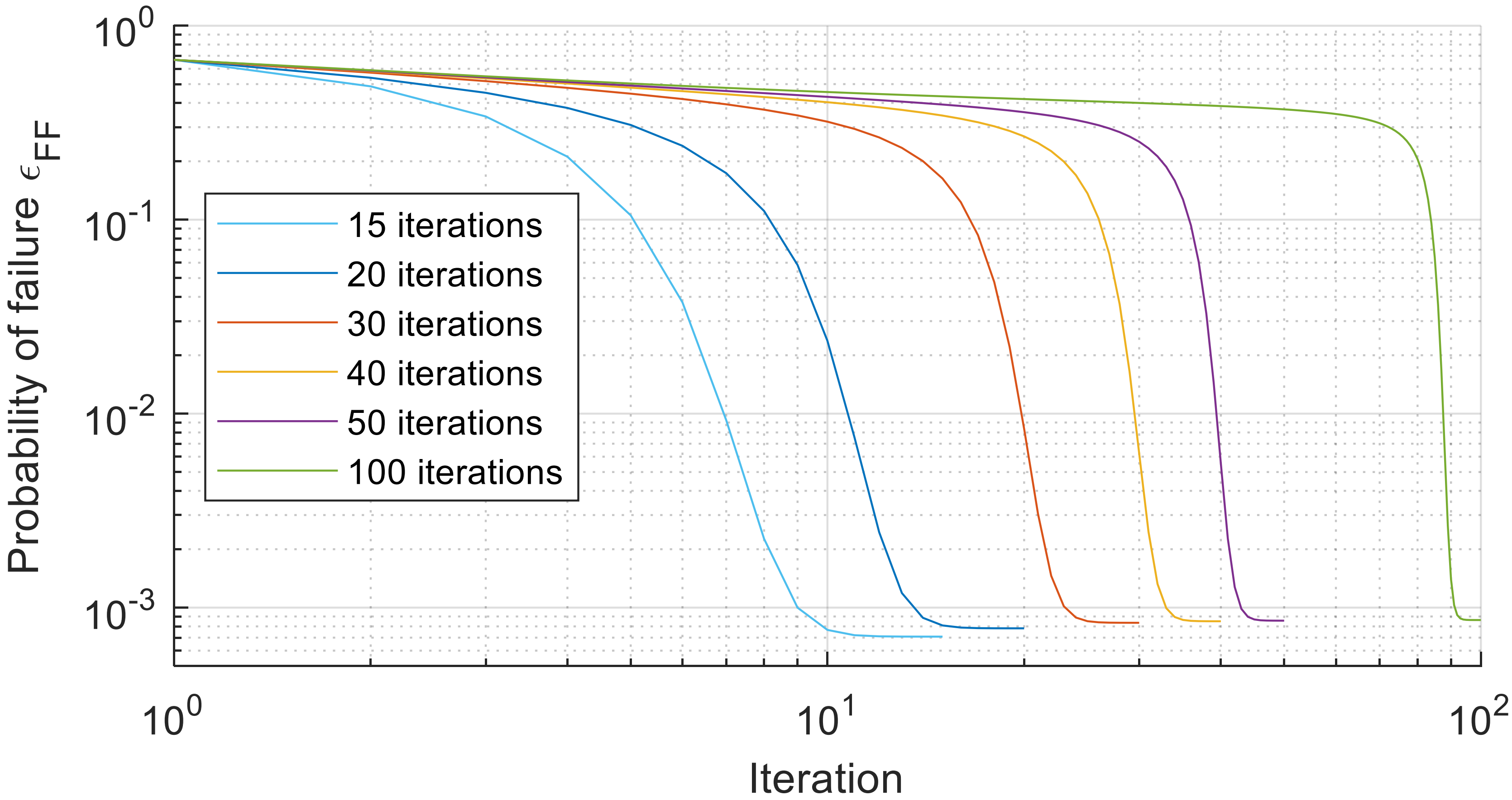
$$a_R \leq \frac{m-1}{\beta_{FB}} = 4.32$$

Asymptotic Performance of 2-degree Quasi-regular Right Degree Distribution from Density Evolution

- $\lambda(x) = x^3, \rho(x) = \alpha x^2 + (1-\alpha)x^3$, assume infinite large bipartite graphs

	α	a_R	β_{FF}	No. Iterations	% $R_t^{(FB)}$	Codeword Error Rate ϵ_{FF}
Regular →	1	3	1.333	15	95.0%	7.09×10^{-4}
Irregular	0.531	3.398	1.177	20	96.8%	7.82×10^{-4}
Irregular	0.244	3.699	1.081	30	98.0%	8.35×10^{-4}
Irregular	0.168	3.788	1.056	40	98.3%	8.50×10^{-4}
Irregular	0.139	3.823	1.046	50	98.4%	8.56×10^{-4}
Irregular	0.108	3.861	1.036	100	98.6%	8.63×10^{-4}

Asymptotic Performance of 2-degree Quasi-regular Right Degree Distribution from Density Evolution



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Non-binary Low Density Parity Check (NB-LDPC) Code as VL Code [Vakilinia et al. ISIT 2014]

VL encoder

k=24 symbols, n=32, Rate-3/4, GF(256) NB-LDPC [Davey et al. Comm. Lett. 1998] with bit-by-bit incremental redundancy (IR)

Channel

Binary-input AWGN Channel with SNR=2 dB

VL decoder

Fast Fourier transformation based Q-ary sum product algorithm (FFT-QSPA) [MacKay et al. IMA 2000] with IR

NB-LDPC VL Code parameters with Constant-size Increments

-

$\boldsymbol{\ell_0}$	$\boldsymbol{\ell_\Delta}$ **for** $\boldsymbol{m = 5}$ **(four increments)**	**Throughput Rate** $R_t^{(FB)}$ **with ACK/NACK Feedback**	**Percentage of Capacity of 2dB BI-AWGN**
302 bits	36 bits	0.5705	88.85%

- $\boldsymbol{\delta} = \{0.309, 0.464, 0.194, 0.0293, 0.00318, 0.00049\}$

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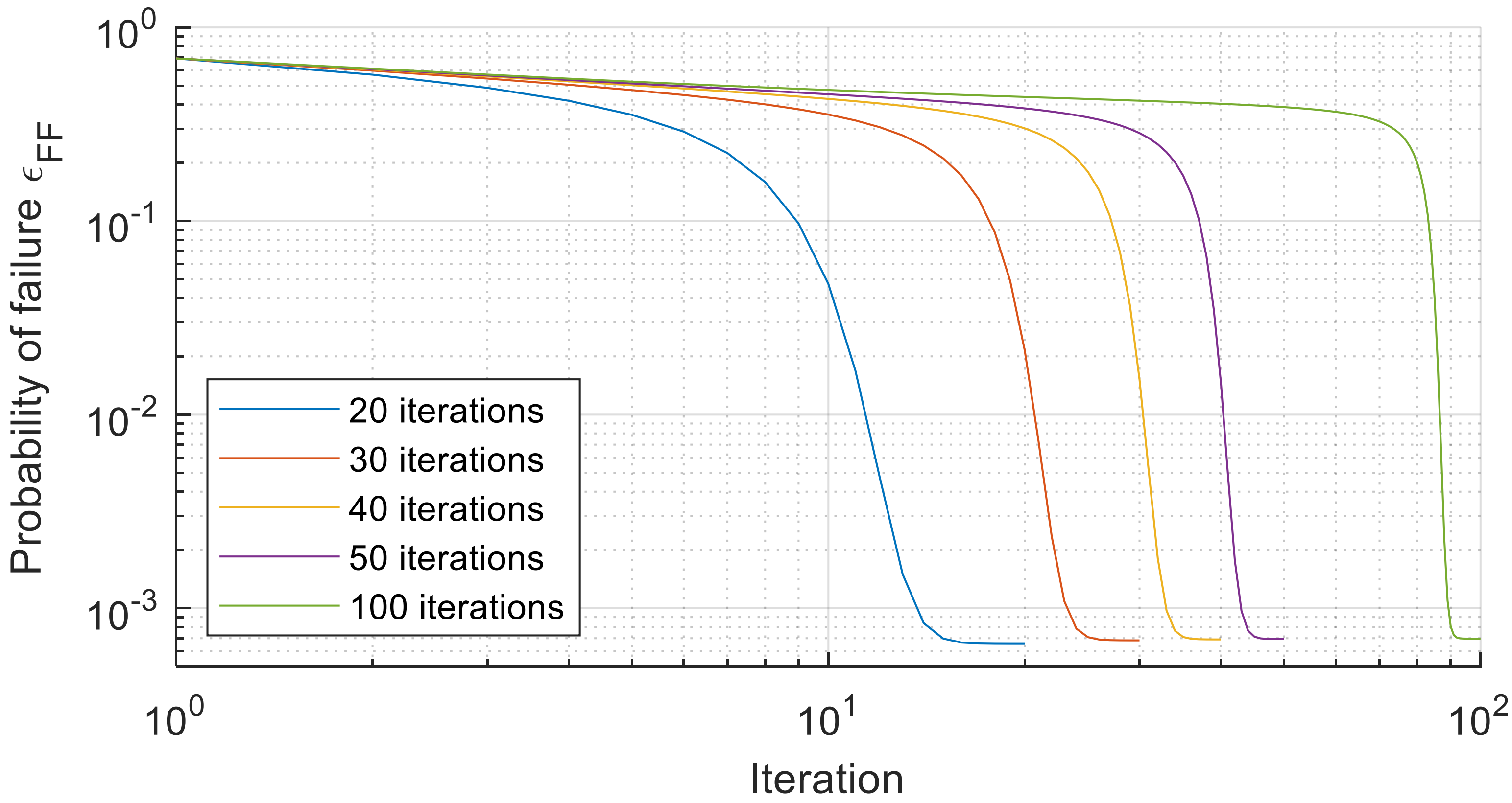
Asymptotic Performance of 2-degree Quasi-regular Right Degree Distribution from Density Evolution

- $\lambda(x) = x^3, \rho(x) = \alpha x^2 + (1-\alpha)x^3$, assume infinite large bipartite graph

α	a_R	β_{FF}	No. Iterations	% $R_t^{(FB)}$	Codeword Error Rate ϵ_{FF}
0.597	3.336	1.199	20	97.4%	6.55×10^{-4}
0.341	3.591	1.114	30	98.3%	6.82×10^{-4}
0.273	3.666	1.091	40	98.5%	6.90×10^{-4}
0.246	3.697	1.082	50	98.6%	6.93×10^{-4}
0.217	3.730	1.072	100	98.7%	6.97×10^{-4}

Asymptotic Performance of 2-degree Quasi-regular Right Degree Distribution from Density Evolution



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Practical Constraints When Designing An Inter-frame Code

- Complexity: Number of systematic nodes n_c
- Error Performance: Probability of error ϵ_{FF}
- Latency: Number of iterations

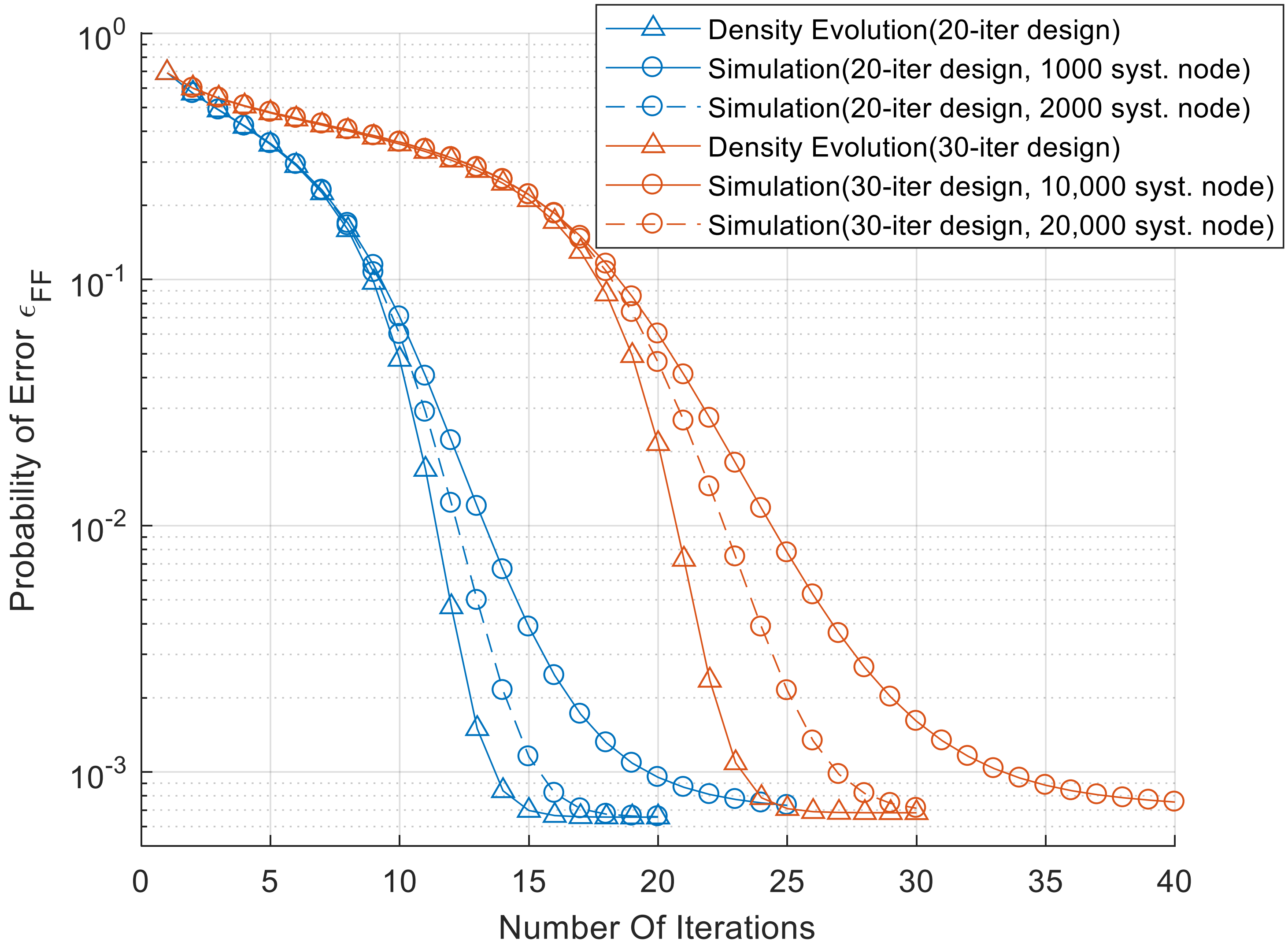
Trade-offs among the constraints!

Number of Systematic Nodes Required of 2-degree Quasi-regular Right Degree Distribution

- $\lambda(x) = x^3, \rho(x) = \alpha x^2 + (1-\alpha)x^3$, 100 inter-frame code iterations

	$\boldsymbol{\alpha = 0.597}$	$\boldsymbol{\alpha = 0.341}$
Throughput rate	0.5559	0.5609
Percentage of Capacity of 2dB BI-AWGN	86.57%	87.35%
Number of Systematic Nodes Needed to Achieve the Designed Throughput Rate	1000	10,000

Probability of Error for Different Designs Requiring Varying Number of Systematic Nodes



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Conclusions

- VL codes with ACK/NACK feedback can approach capacity with short blocklengths.
- We used many short blocklength VL codes in parallel *without feedback* to achieve 98% of throughput of the underlying VL codes with feedback.
- Inter-frame coding enables a distributed decoding architecture for very high throughputs.

Projects

- Reliability/Latency/Throughput: ECC Parallelization and Incremental Redundancy

- Lifetime: Channel Estimation and Write Voltage Optimization

Histogram-Based Flash Channel Estimation and Dynamic Voltage Allocation

Haobo Wang, Tsung-Yi Chen, Richard D. Wesel

Motivation

- How to reduce Flash memory's wear-out?

Write to lower threshold voltages!

Outline

- Channel Model
- Channel Parameter Estimation
- Dynamic (Write) Voltage Allocation

Channel Model

- We model the NAND flash memory cell data storage process as

$$y = x + n_p + n_w + n_r$$

y : sensed programmed state threshold voltage

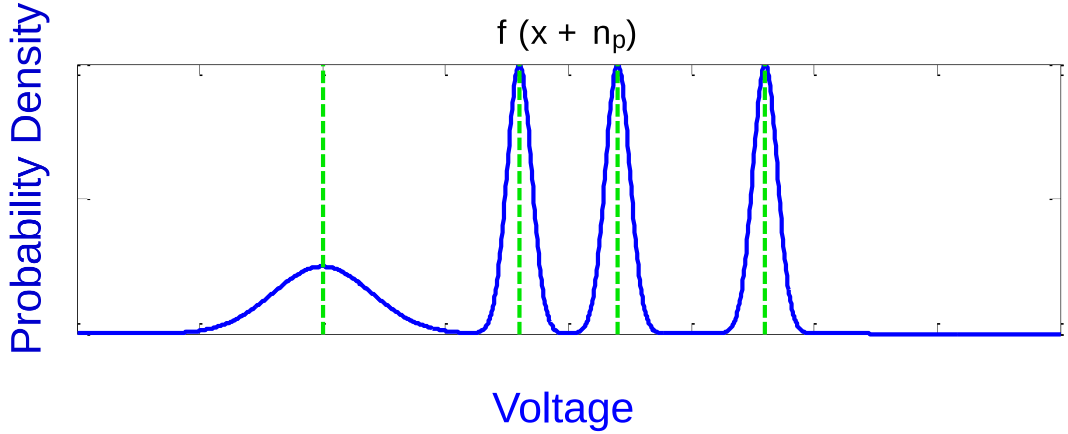
x : intended programmed state threshold voltage

n_p : programming noise

n_w : wear-out noise

n_r : retention noise

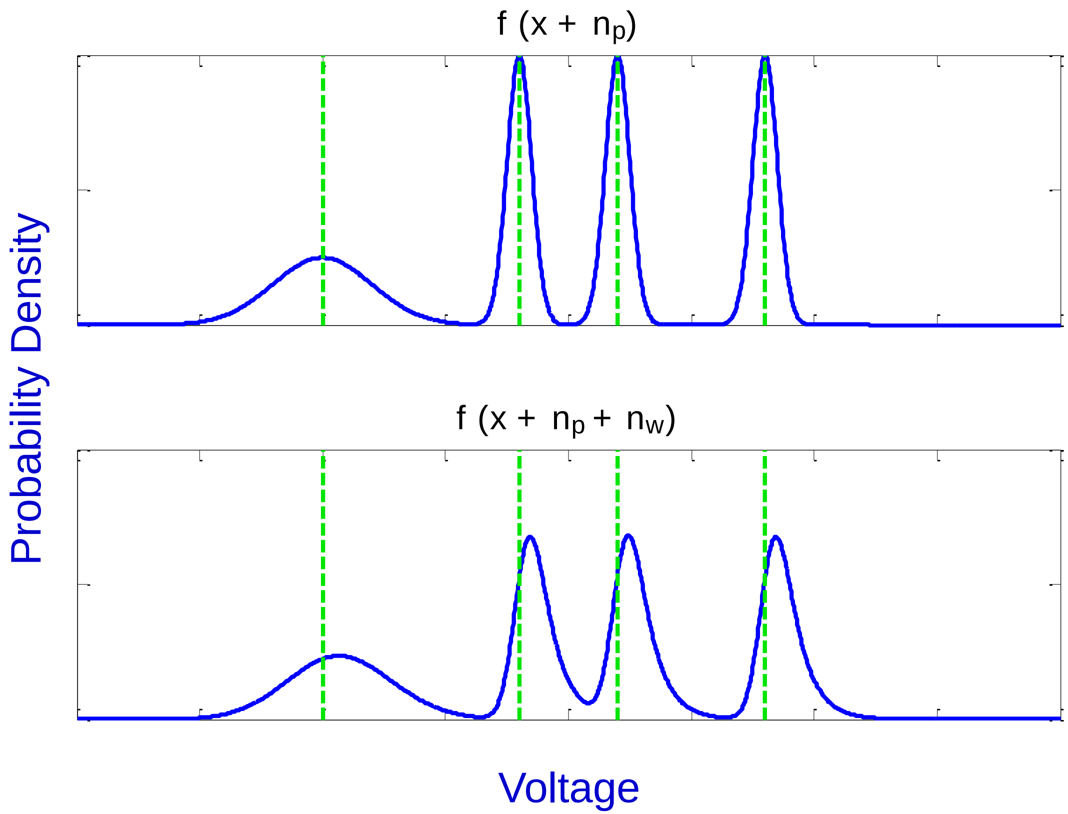
Programming Noise (n_p)



Programming Noise Only $f(n_p)$

$$f(n_p) = \begin{cases} N(0, \sigma_e^2) & \text{if } x = 0 \\ N(0, \sigma_p^2) & \text{if } x > 0 \end{cases} \quad \text{where } \sigma_e > \sigma_p$$

Wear-out Noise (n_w)



Programming Noise Only $f(n_p)$

Programming and Wear-out Noise

$f(n_p) \otimes f(n_w)$

$$f(n_w) = \begin{cases} \frac{1}{\lambda} e^{-\frac{n_w}{\lambda}} & n_w \geq 0 \\ 0 & n_w < 0 \end{cases}$$

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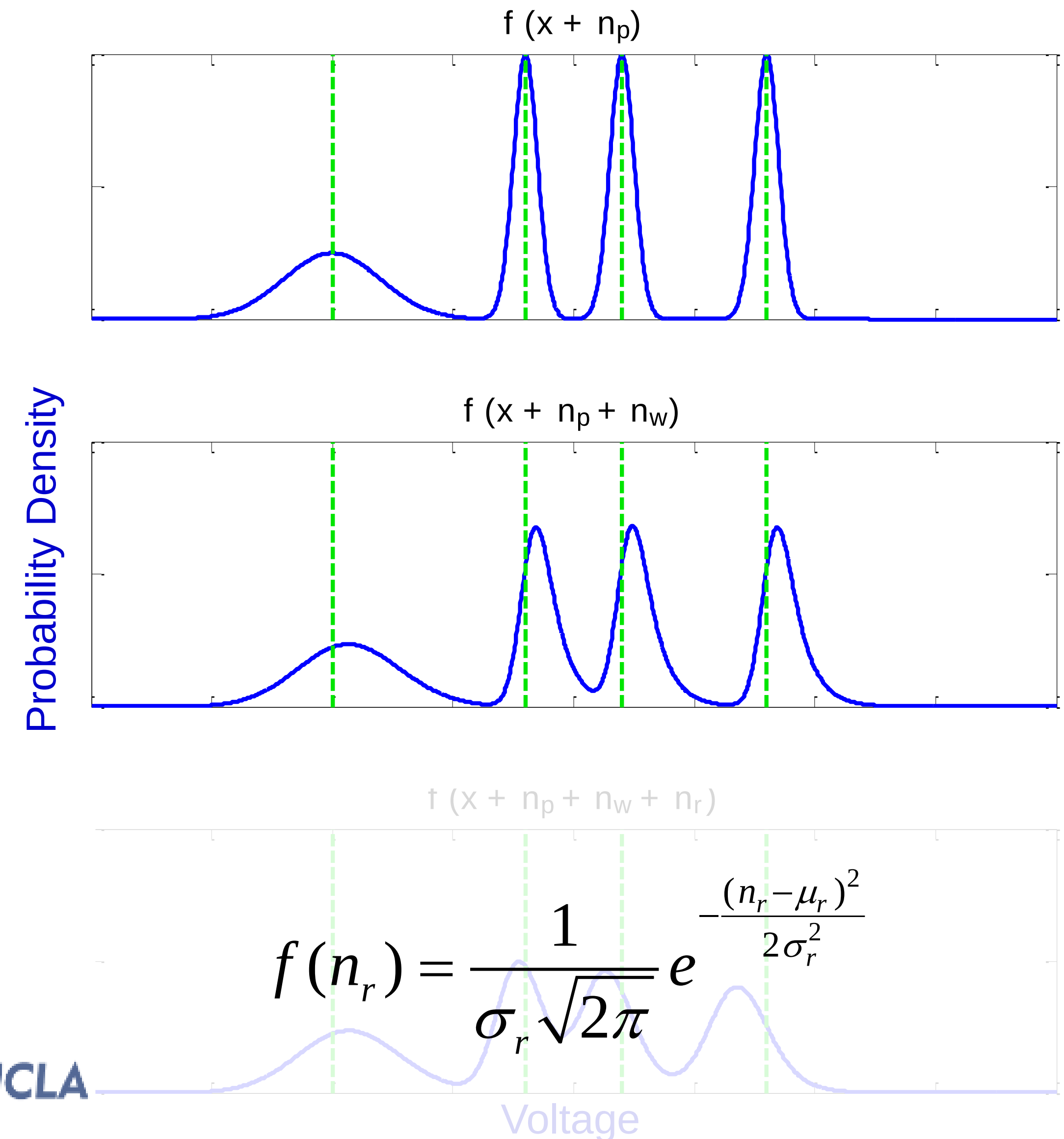
Retention Noise (n_r)



Programming Noise Only
$f(n_p)$

Programming and Wear-out Noise
$f(n_p) \otimes f(n_w)$

Programming, Wear-out and Retention Noise
$f(n_p) \otimes f(n_w) \otimes f(n_r)$

$$f(n_r) = \frac{1}{\sigma_r \sqrt{2\pi}} e^{-\frac{(n_r - \mu_r)^2}{2\sigma_r^2}}$$

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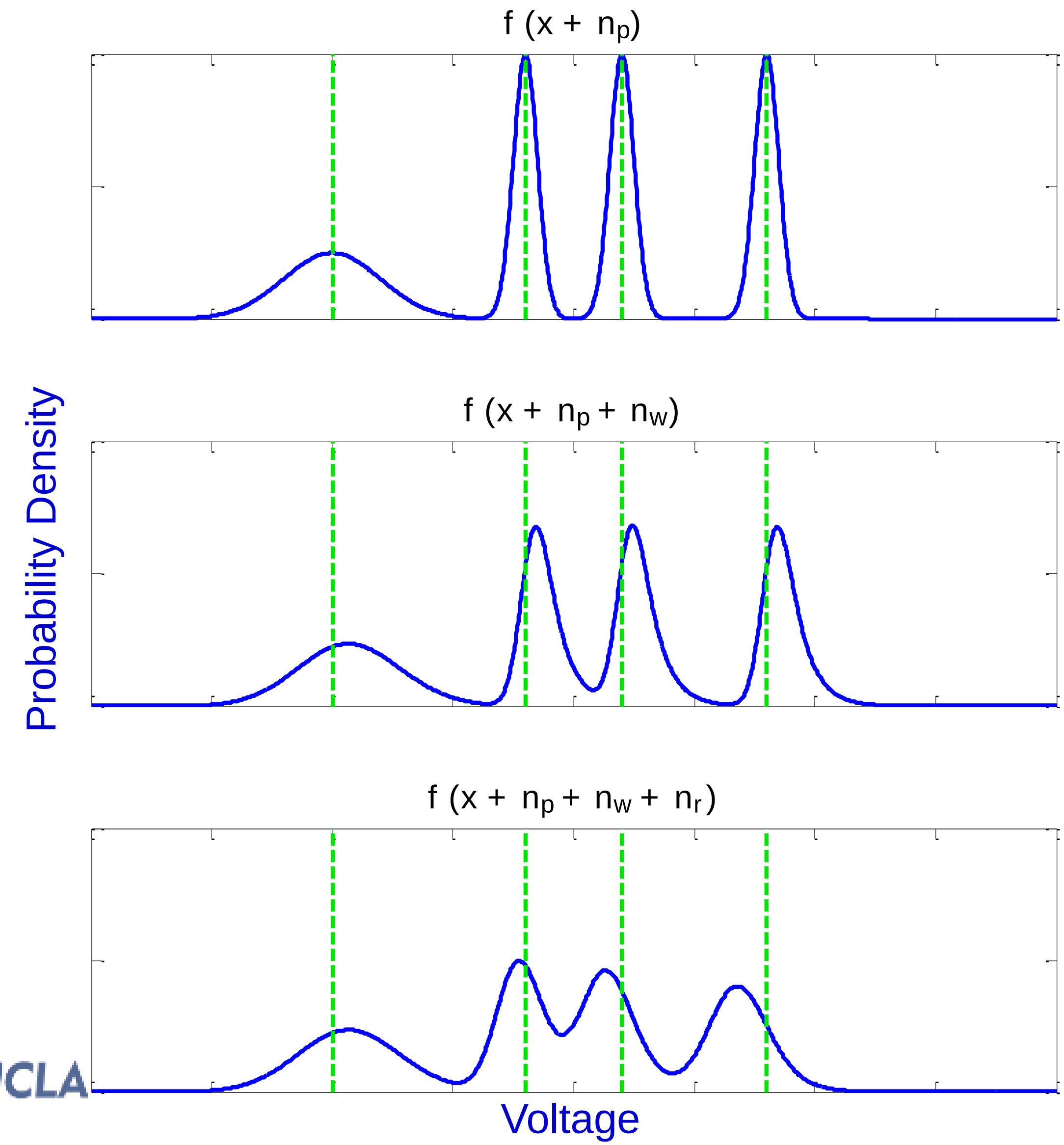
Sample PDF



Programming Noise Only

$f(n_p)$

Programming and Wear-out Noise

$f(n_p) \otimes f(n_w)$

Programming, Wear-out and Retention Noise

$f(n_p) \otimes f(n_w) \otimes f(n_r)$

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Replace number of P/E cycles with accumulated voltage

- Channel degradation is usually modeled as a function of the number of program/erase (P/E) cycles.

Replace number of P/E cycles with accumulated voltage

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- The volume of charge passing through dielectrics actually causes the degradation.

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- The use of the number of P/E cycles is approximately correct when the volume of charge passing through the dielectrics is the same for each P/E cycle.

Replace number of P/E cycles with accumulated voltage

- Channel degradation is usually modeled as a function of the number of program/erase (P/E) cycles.
- The volume of charge passing through dielectrics actually causes the degradation.
- The use of the number of P/E cycles is approximately correct when the volume of charge passing through the dielectrics is the same for each P/E cycle.
- We use a more precise metric named accumulated voltage Vacc to directly characterize the volume of charge that has passed since the first write.

Accumulated Voltage

$$V_{acc} = \sum_{j=1}^{N} \left(V_p^{(j)} - V_e \right)$$

V_{acc} : accumulated voltage over N P/E cycles,

$V_p^{(j)}$: programmed threshold voltage of the jth P/E cycle

V_e : threshold voltage of the erased state

The normalized accumulated voltage is $V_{acc} / V_{\max}$, where $V_{\max}$ is the maximum of $V_p^{(j)} - V_e, \forall j.$

When using fixed voltage levels, $V_{acc} / V_{\max}$ ≈ # PE Cycles.

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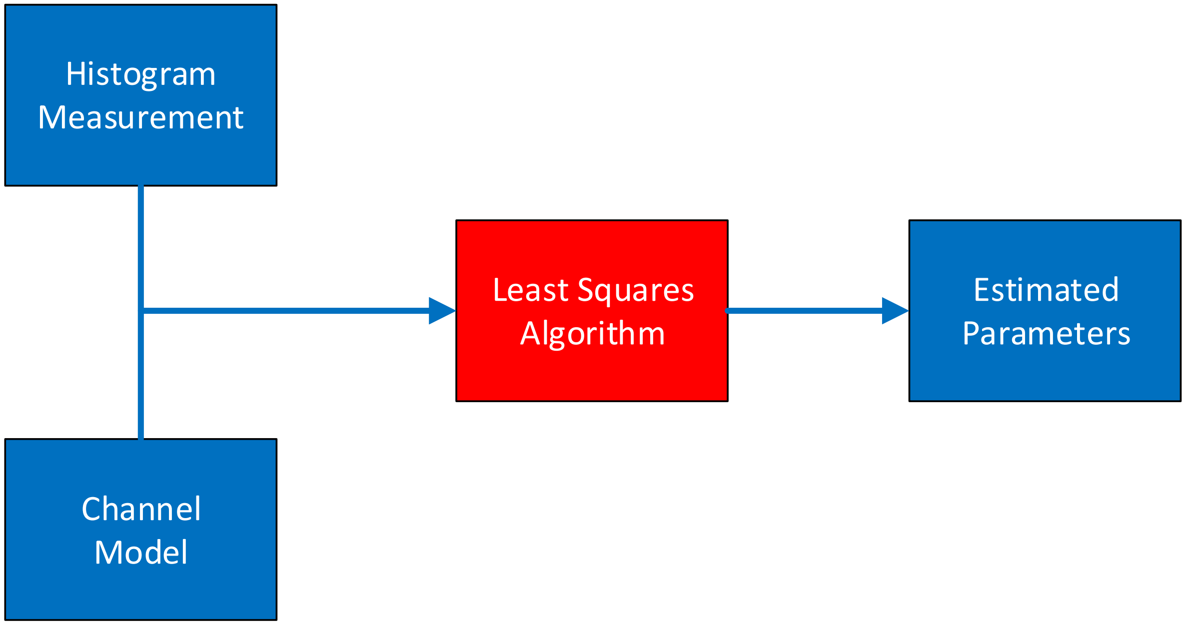
Channel Parameter Estimation

- Channel parameter estimation workflow:



Parameter Vector

- $[\lambda, \sigma_{\text{programming}}, \sigma_{\text{erase}}, \sigma_{\text{retention}}, \mu_{\text{retention}}]$

- We actually estimate $[\lambda, \sigma_p, \sigma_e, m_r, n_r]$, where

$$\mu_{\text{retention}} = (x - x_0) \cdot n_r$$
$$\sigma^2_{\text{retention}} = (x - x_0) \cdot m_r^2 \quad .$$

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Estimation Objective Function

- Estimation Objective Function is the squared Euclidean distance between the predicted histogram and measured histogram

$$C_M = \sum_{i=0}^{M-1} \left(\frac{\hat{N}_{\mathrm{bin,i}} - N_{\mathrm{bin,i}}}{N} \right)^2$$

N : total number of cells in a page

$N_{\mathrm{bin,i}}$: total number of cells in ith bin of measure histogram

$\hat{N}_{\mathrm{bin,i}}$: total number of cells in ith bin by estimation

M : total number of bins

More about Least Squares Algorithms

- Objective
  - Minimize the cost function: $C_M = \sum_{i=0}^{M-1} \left(\frac{\hat{N}_{\text{bin,i}} - N_{\text{bin,i}}}{N} \right)^2$

More about Least Squares Algorithms

- Objective
  - Minimize the cost function: $C_M = \sum_{i=0}^{M-1} \left(\frac{\hat{N}_{\mathrm{bin,i}} - N_{\mathrm{bin,i}}}{N} \right)^2$
- Algorithm 1 – Gradient Descent
  - Follow the descending gradient with a fixed step size.

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More about Least Squares Algorithms

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- Algorithm 2 – Gauss–Newton Algorithm
  - Take each step based on quadratic approximation at current point.

More about Least Squares Algorithms

- Objective
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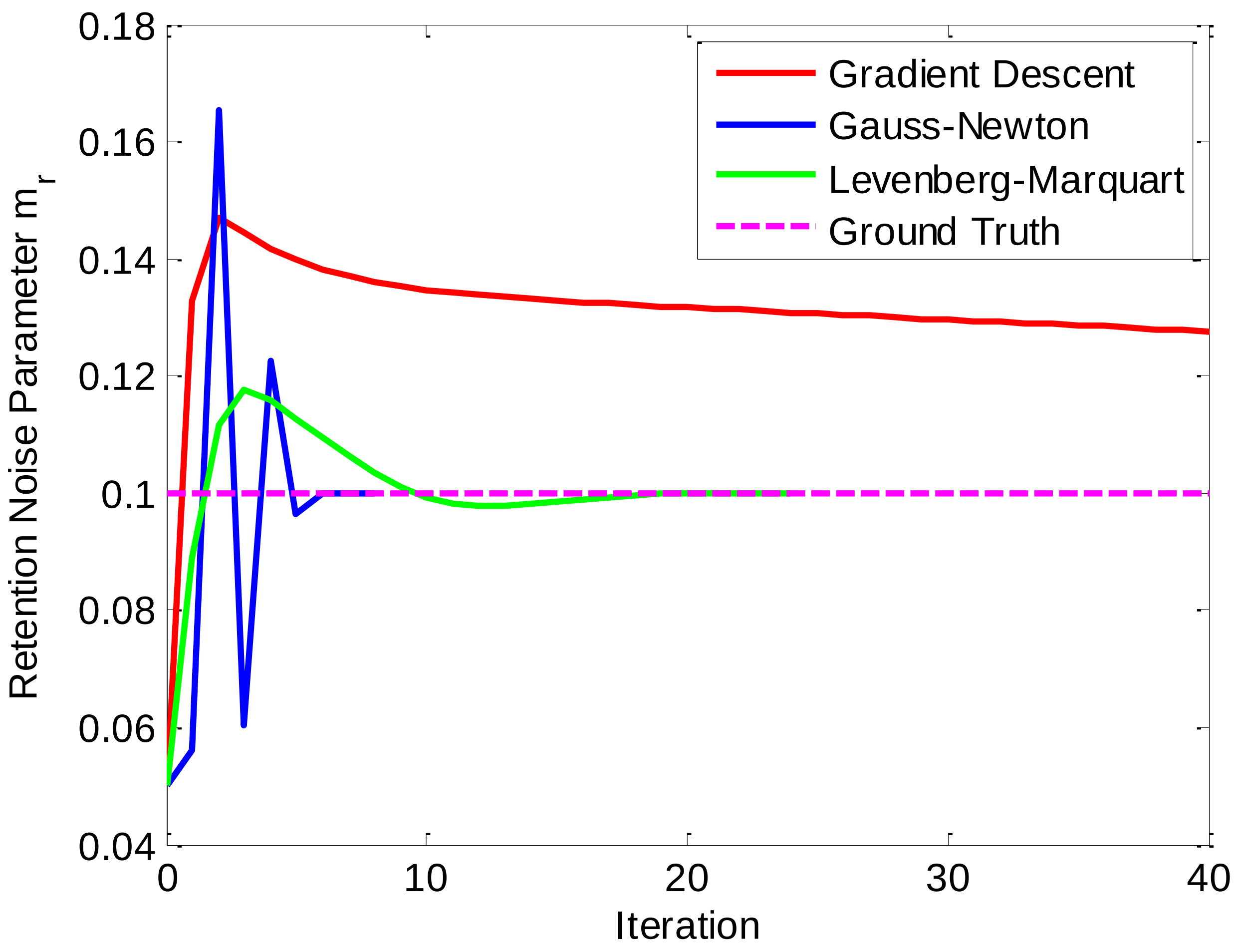
- Algorithm 1 – Gradient Descent
  - Follow the descending gradient with a fixed step size.
- Algorithm 2 – Gauss–Newton Algorithm
  - Take each step based on quadratic approximation at current point.
- Algorithm 3 – Levenberg–Marquardt Algorithm
  - Rotate Gauss-Newton increment vector toward the direction of descending gradient.

Least Squares Algorithm Speed Comparison



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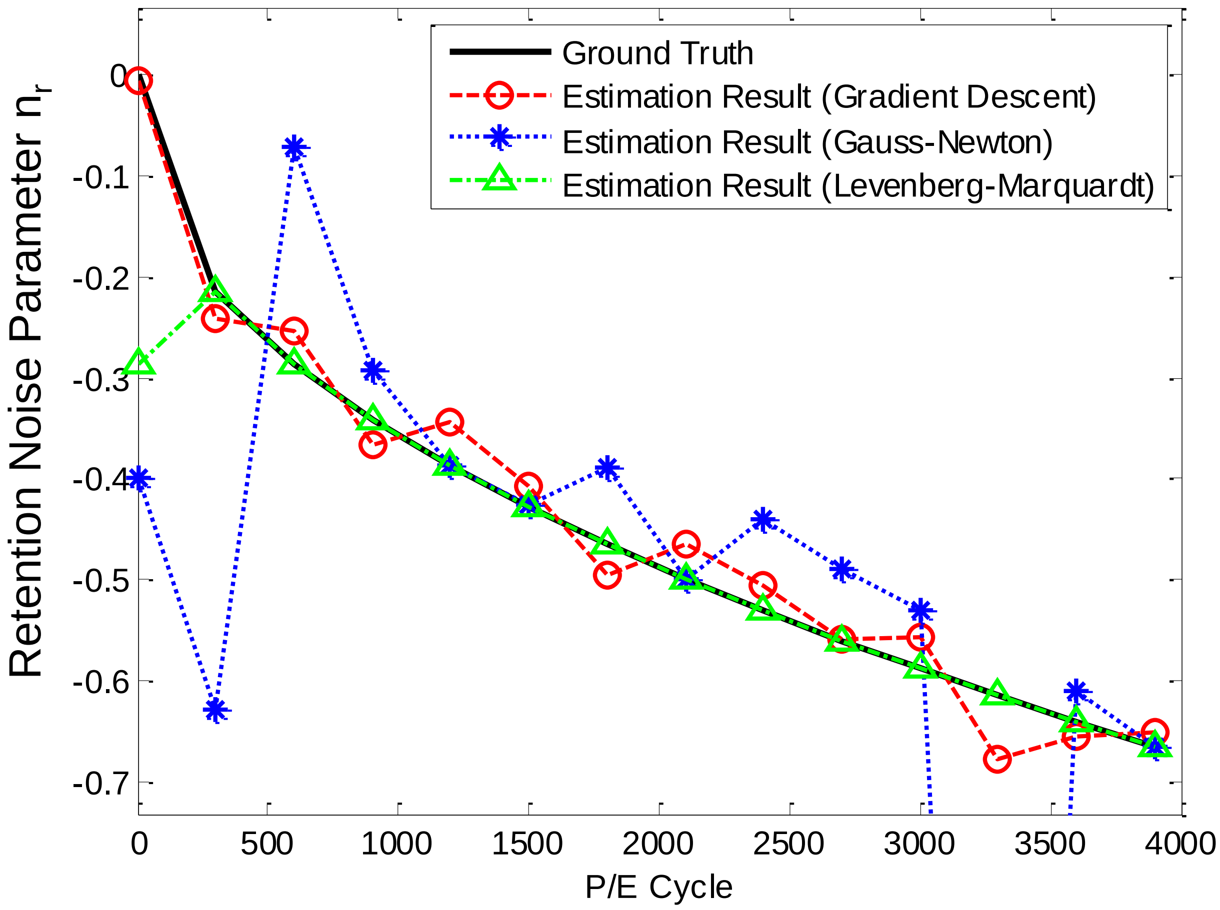
Least Squares Algorithm Accuracy Comparison



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Least Squares Algorithms Choice

- Algorithm 1 – Gradient Descent
  - Convergence speed is too slow.
- Algorithm 2 – Gauss–Newton Algorithm
  - Converge fast but lacks stability.
- Algorithm 3 – Levenberg–Marquardt Algorithm
  - Good for parameter estimation.

Binning Strategy

- Bin-placement Paradigm
- Number of Bins

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Bin-placement Paradigm

- Equal Interval (EI) Histogram
  - Not actually equal. Bins covering erased state distribution can be slightly wider.

- Maximum Mutual Information (MMI) Histogram
  - Bins optimized for decoding.

- Equal Probability (EP) Histogram
  - Each bin has the same number of cells.

One metric to consider…

- Squared Euclidean Distance between the Channel distribution $f(y)$ and the histogram induced by $f(y)$.

$$D_{E^2} = \sum_{i=0}^{M-1} \int_{q_i}^{q_{i+1}} \left(f(y) - \frac{H_i}{q_{i+1} - q_i} \right)^2 dy$$

$f(y)$: channel distribution

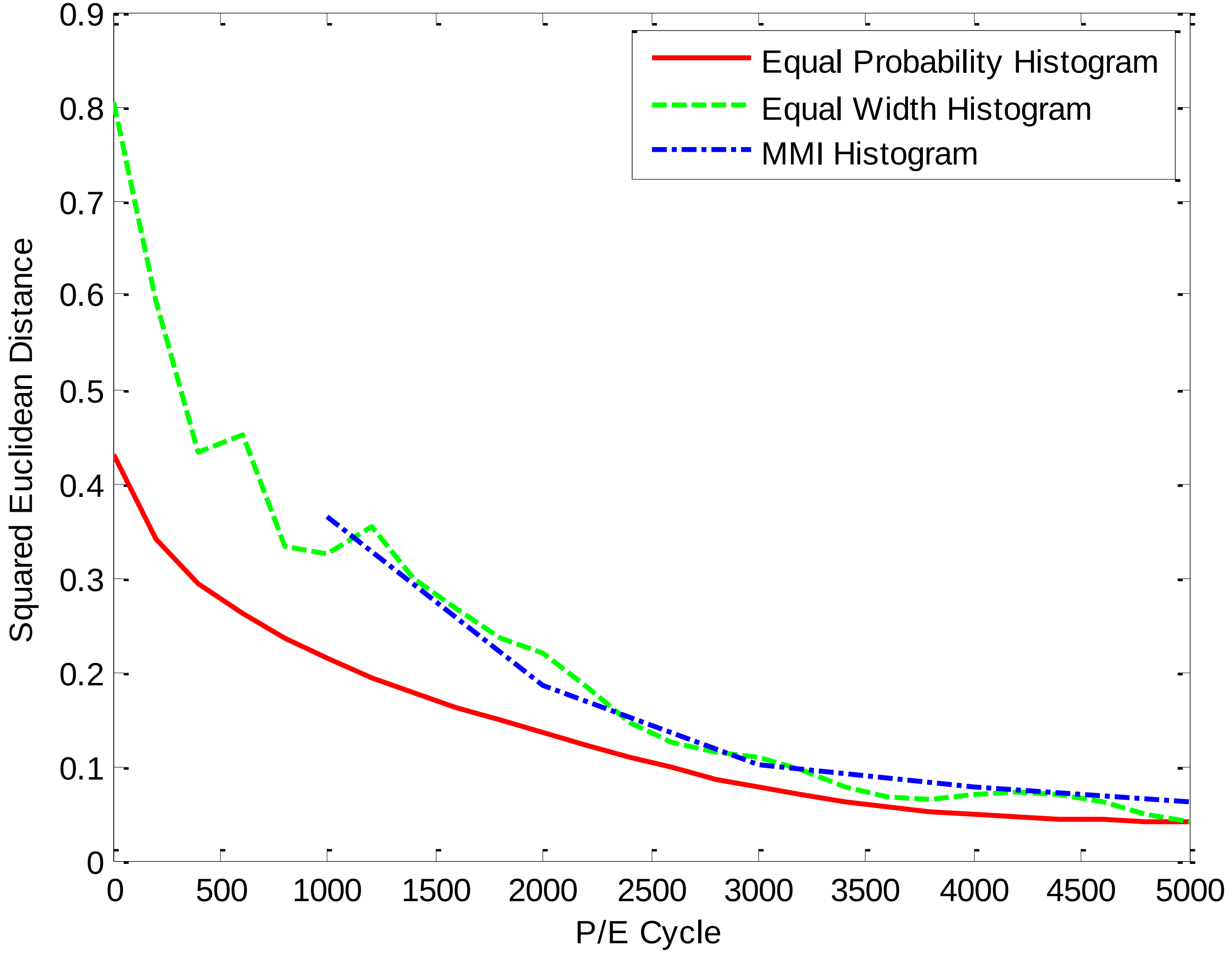
M : number of bins

q_i : left boundary of the ith interval

q_{i+1} : right boundary of the ith interval

H_i : probability of the ith bin $H_i = \int_{q_i}^{q_{i+1}} f(y)dy$

Square Euclidean Distance Comparison



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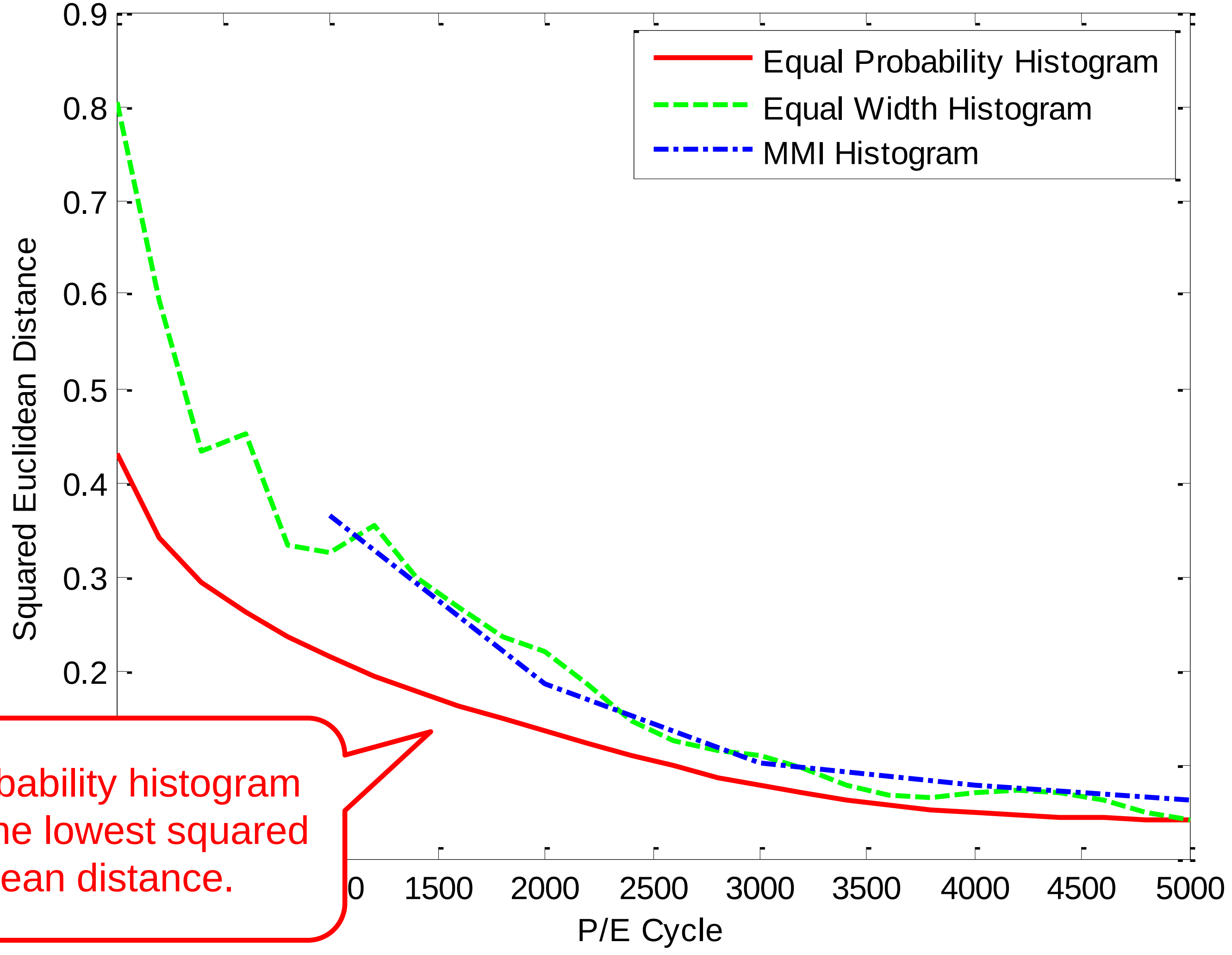
Square Euclidean Distance Comparison



Equal probability histogram provides the lowest squared Euclidean distance.

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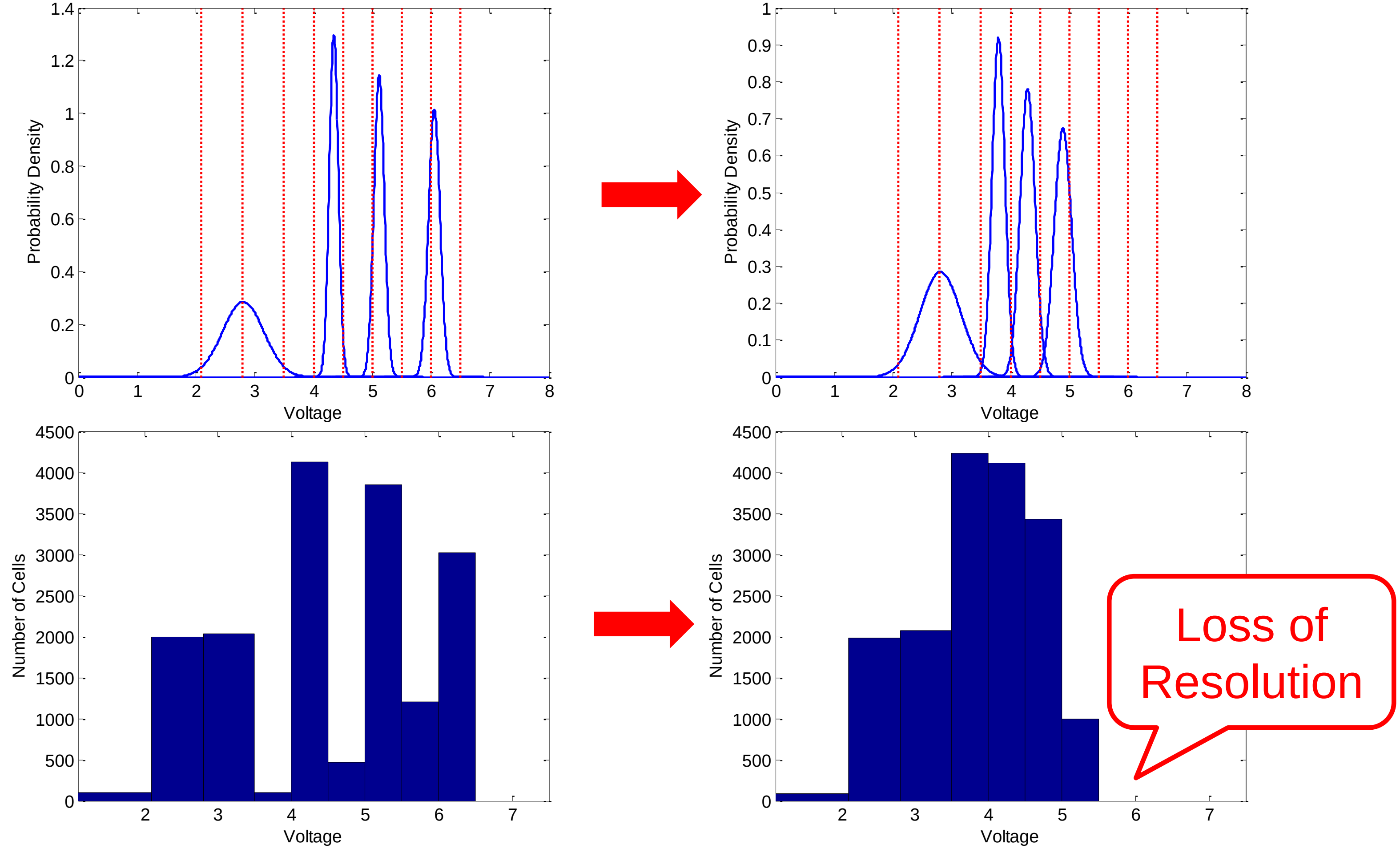
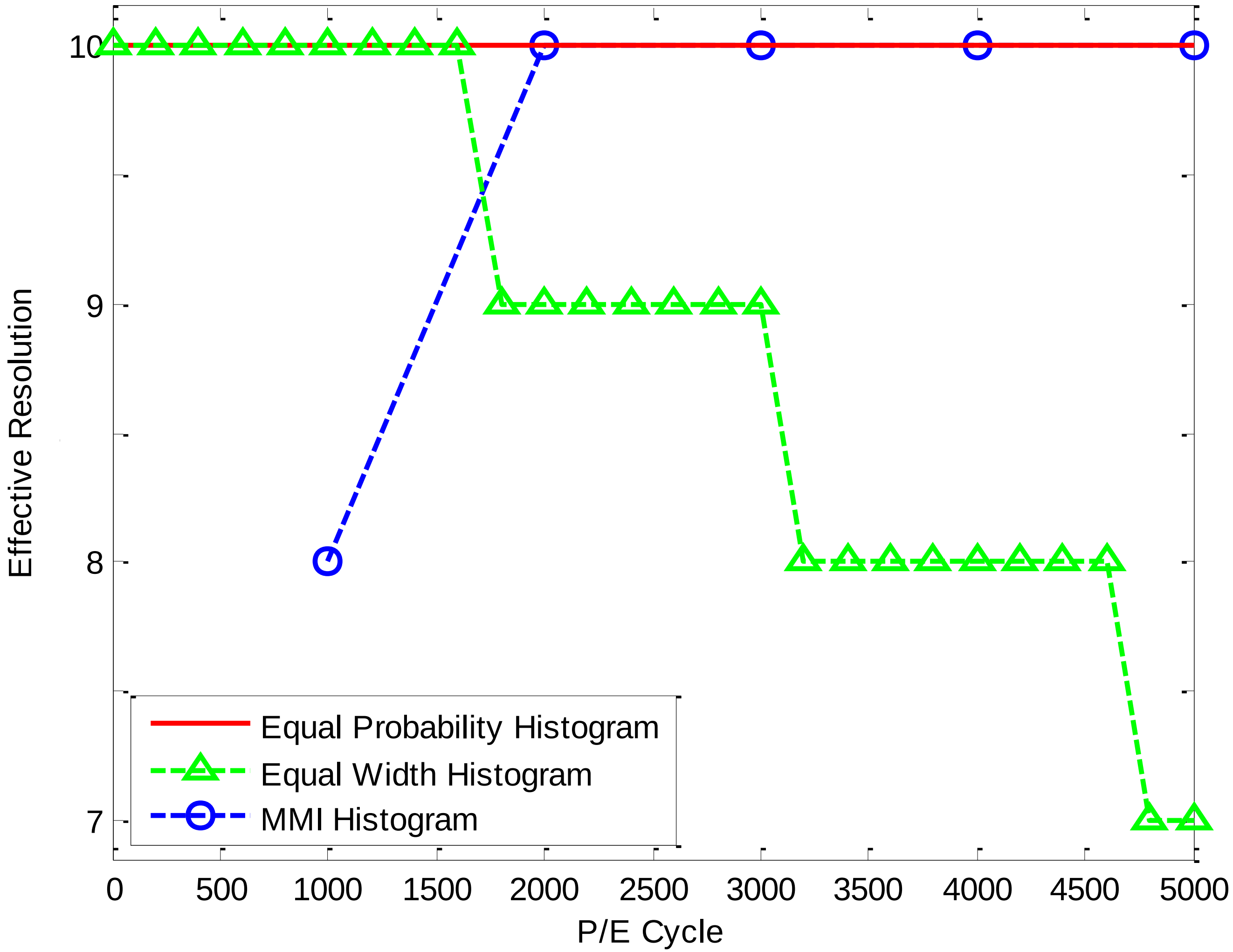
Another metric to consider…

- Effective Resolution
  - Two adjacent zero-height bins can be combined as one bin.
  - Effective resolution is the number of bins after this combination process.

Equal-interval histogram loses resolution with retention effect.



Effective Resolution Comparison



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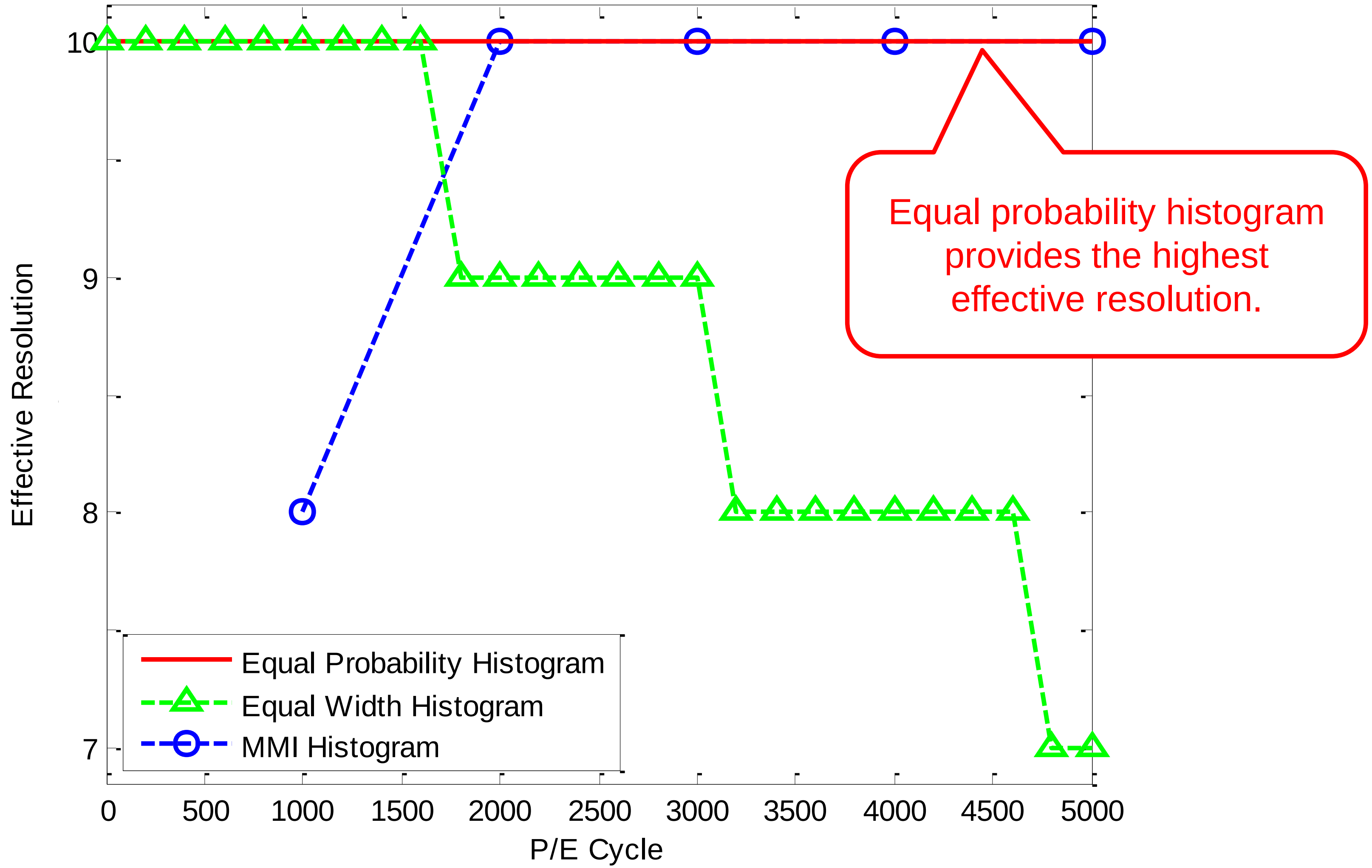
Effective Resolution Comparison



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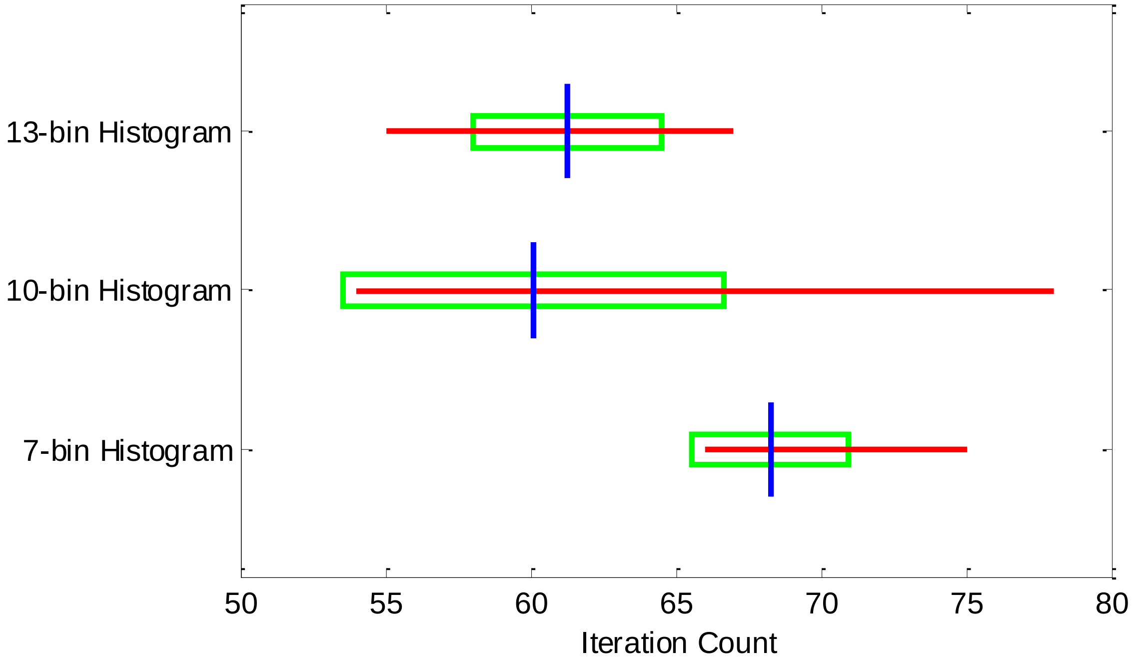
Bin-placement Paradigm Choice

- Equal Interval Histogram
  - Equal interval histogram does not adapt well to retention loss.
- Maximum Mutual Information Histogram
  - This histogram optimizes decoder performance, but may not be the best for channel parameter estimation.
- Equal Probability Histogram
  - Every bin has an equal number of cells, good for parameter estimation.

Number of Bins Comparison



Horizontal Line Segment: Range of Iteration Count

Vertical Line Segment: Mean of Iteration Count

Rectangle: Standard Deviation of Iteration Count

Levenberg-Marquardt Algorithm Iteration Count

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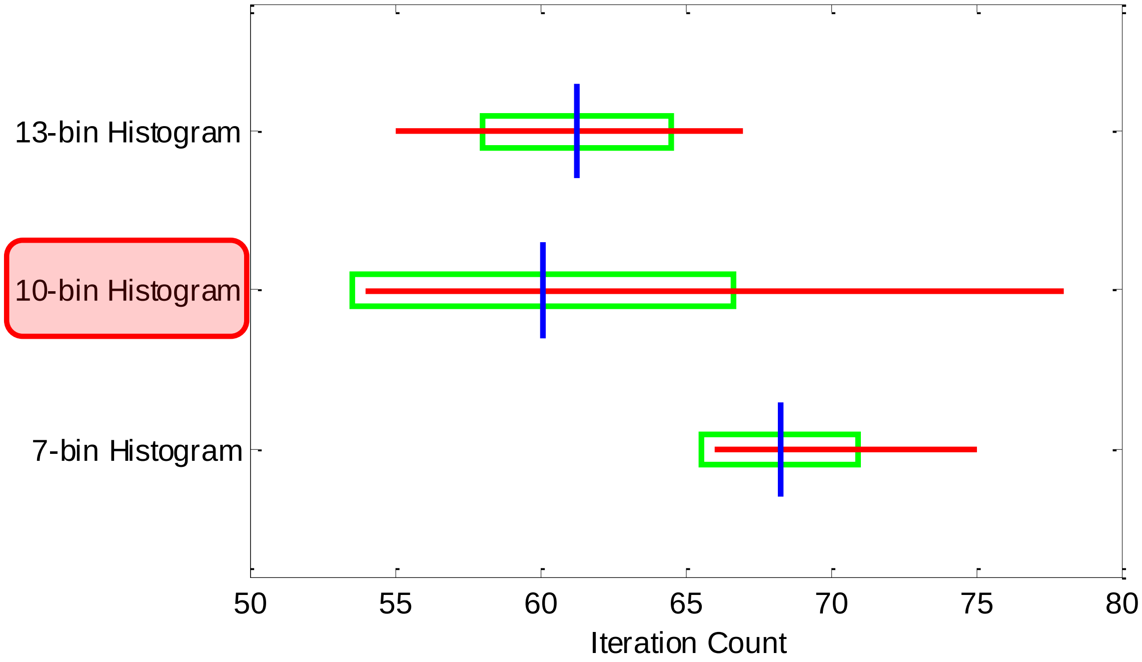
Number of Bins Comparison



Horizontal Line Segment: Range of Iteration Count

Vertical Line Segment: Mean of Iteration Count

Rectangle: Standard Deviation of Iteration Count

Levenberg-Marquardt Algorithm Iteration Count

- 10-bin histogram strikes the right balance, which provides sufficient information to narrow the set of possible channels but not so large as to overstrain the optimization algorithm.

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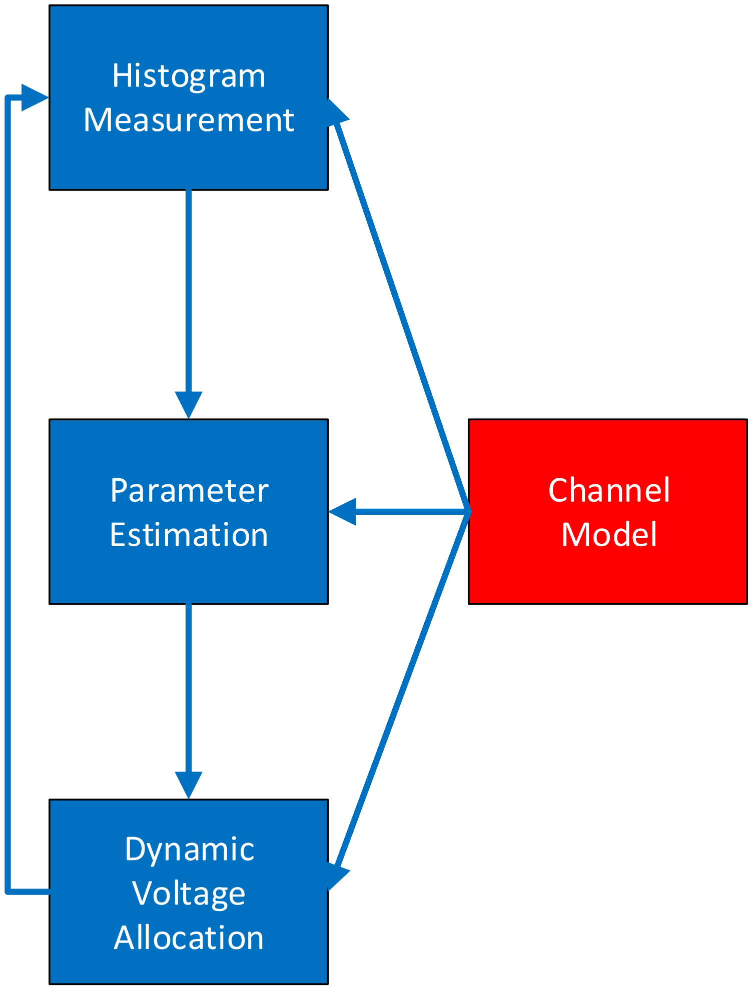
Dynamic (Write) Voltage Allocation

- Fixed threshold voltage allocation provides unnecessary margin at the beginning of Flash memory's lifetime, causing accelerated wear-out.
- Dynamic Voltage Allocation can reduce unnecessary wear-out, and thus increase lifetime by using lower threshold voltages for early writes.
- The threshold voltages can be gradually increased as needed using a single scaling factor to combat channel degradation.
- The target of the anti-degradation process is to maintain a minimum mutual information as long as possible.

DVA using Histogram-based Channel Estimation



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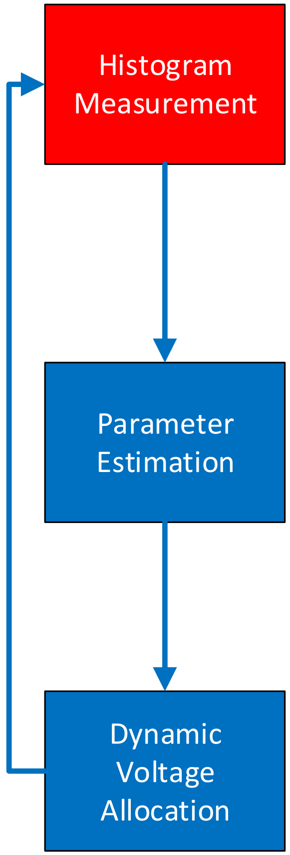
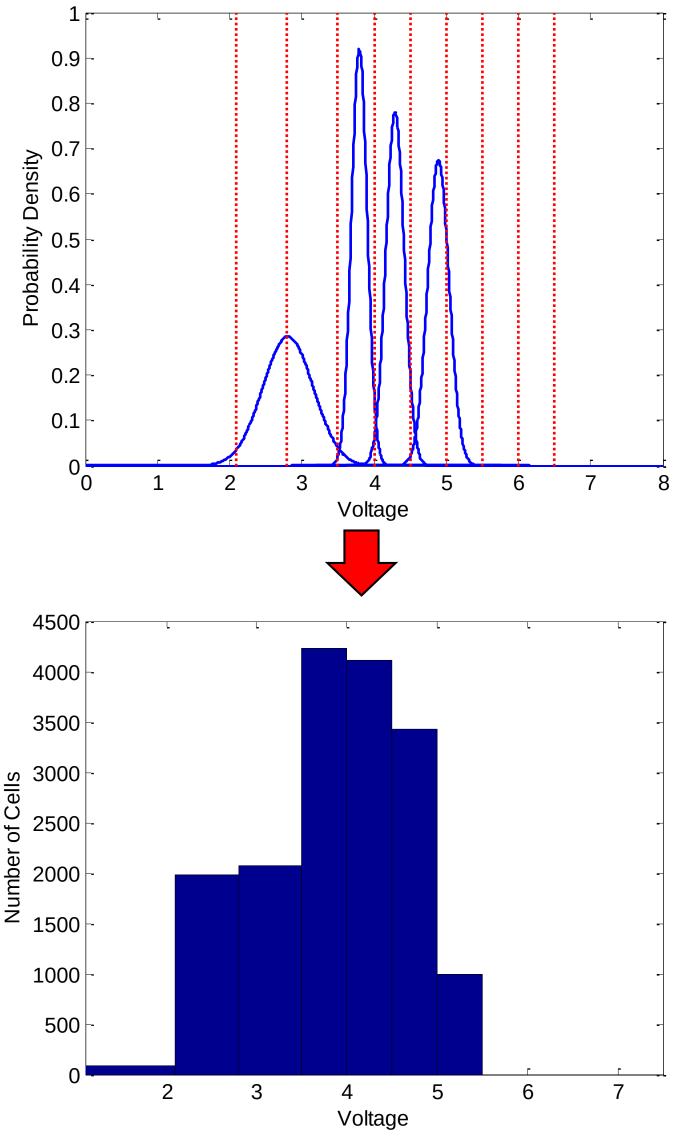
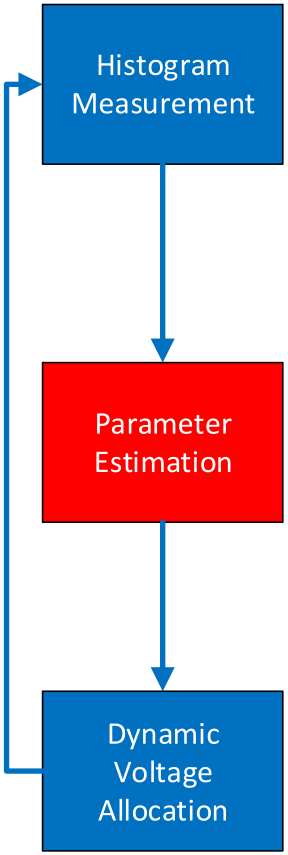
Histogram Measurement

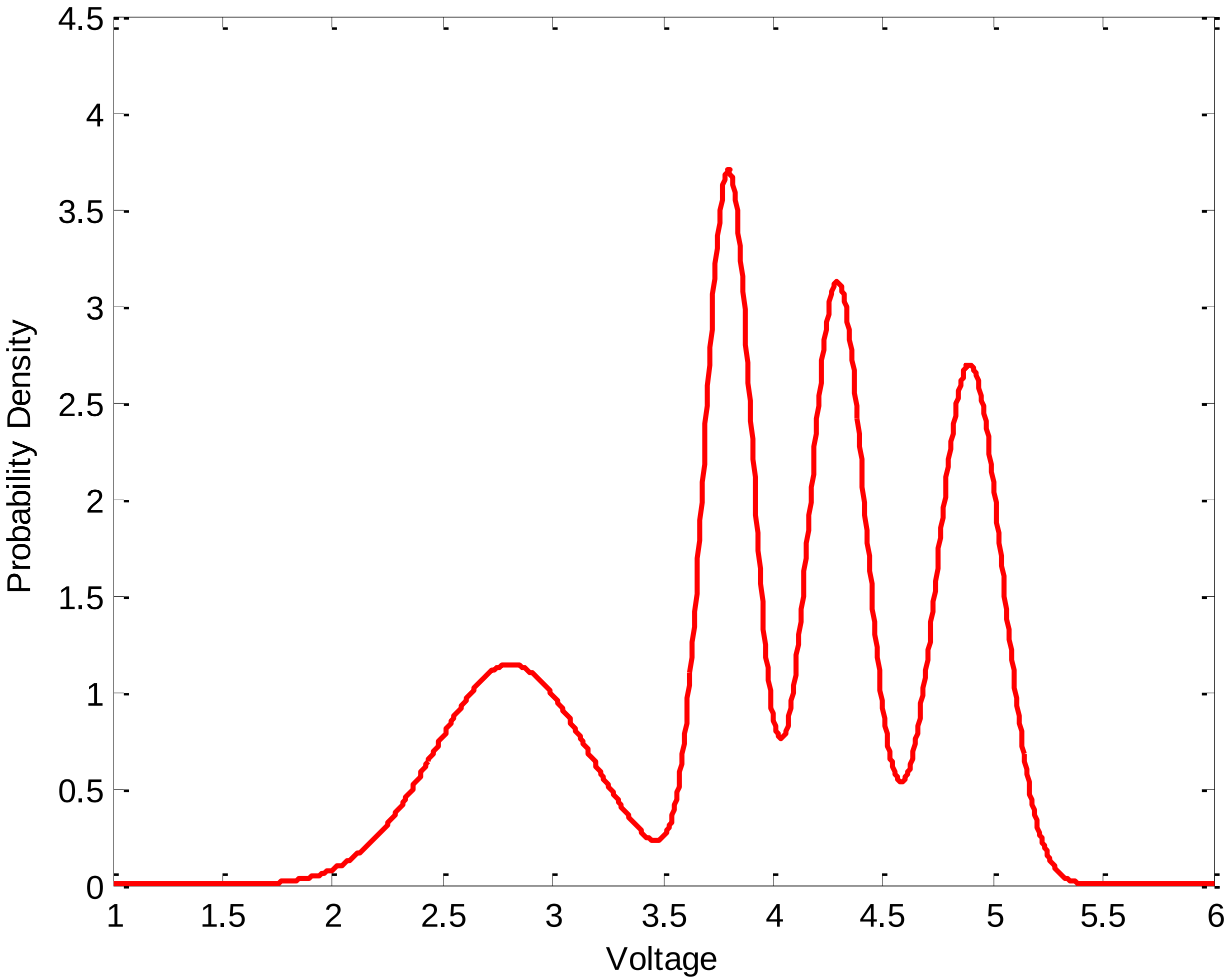




Parameter Estimation



Ground Truth: [0.0099,0.3500,0.0500,0.0617,-0.5882]



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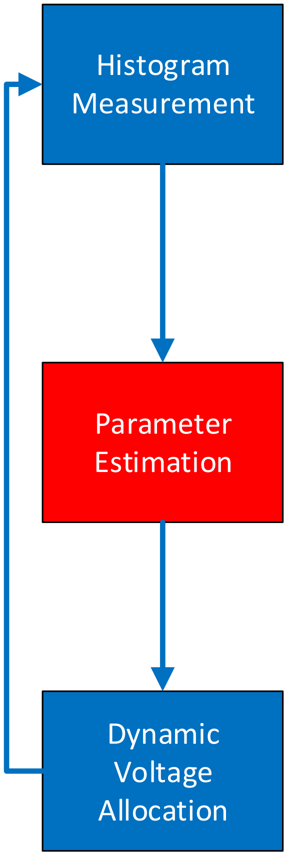
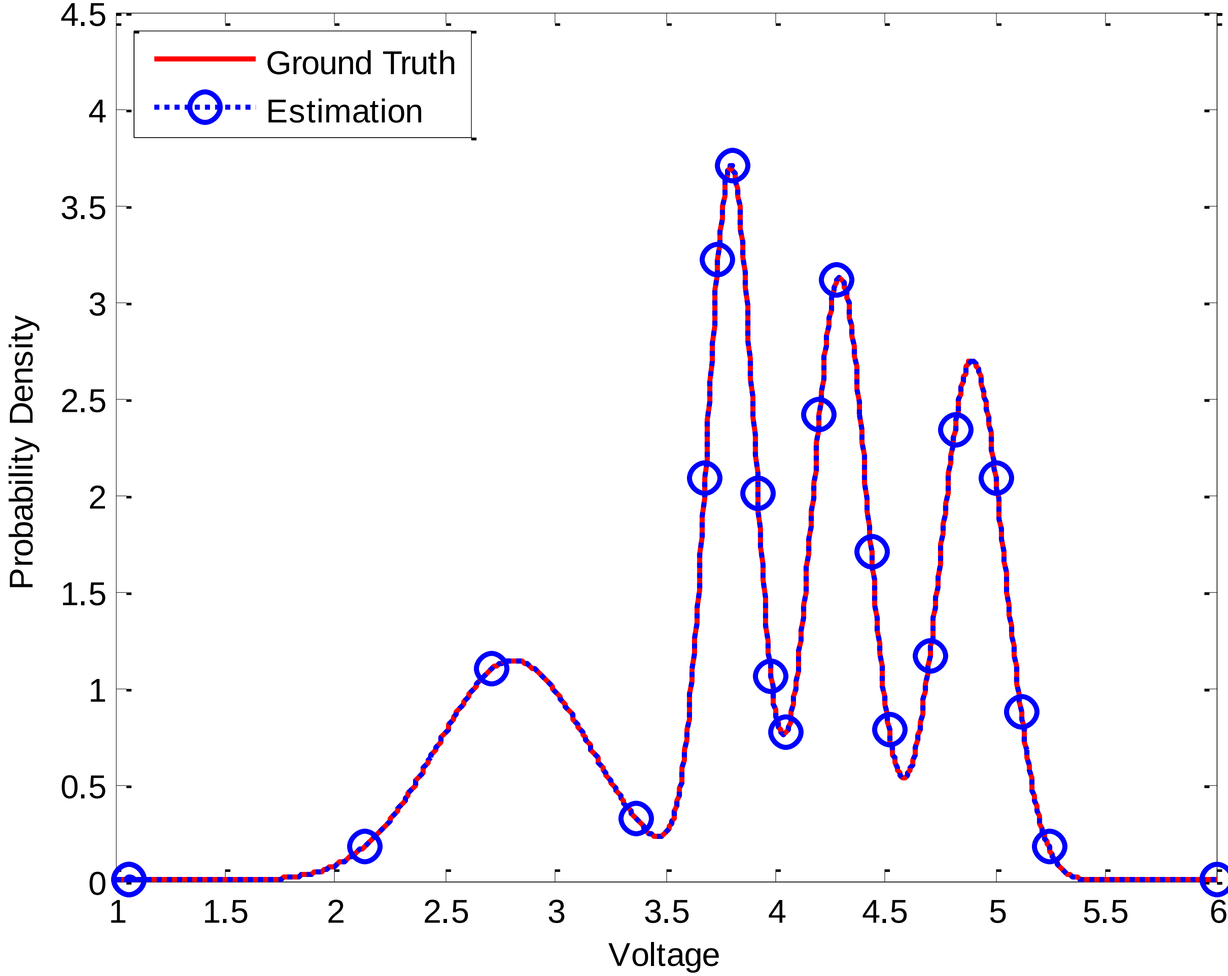
Parameter Estimation



Ground Truth: [0.0099,0.3500,0.0500,0.0617,-0.5882]

Estimation Error: $10^{-4} \times$ [0.0101 0.0214 -0.1774 0.0405 -0.0044]



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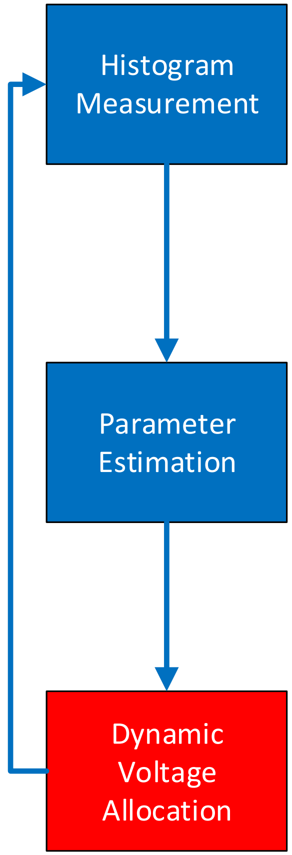
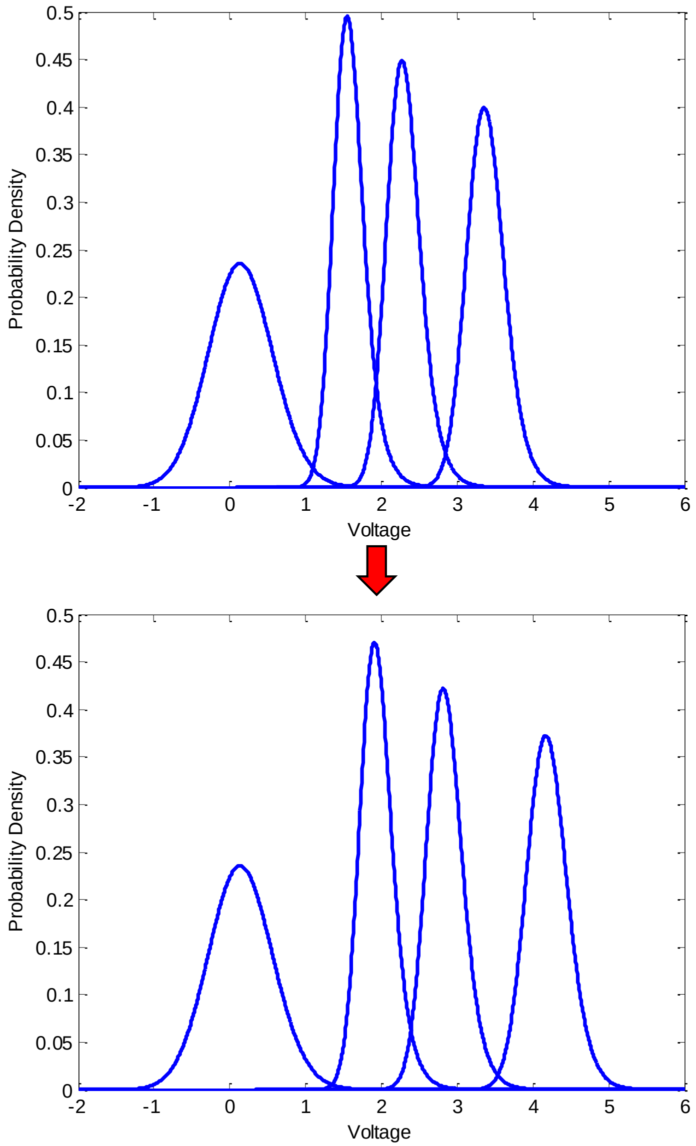
Voltage Levels Adapted to Degraded Channel





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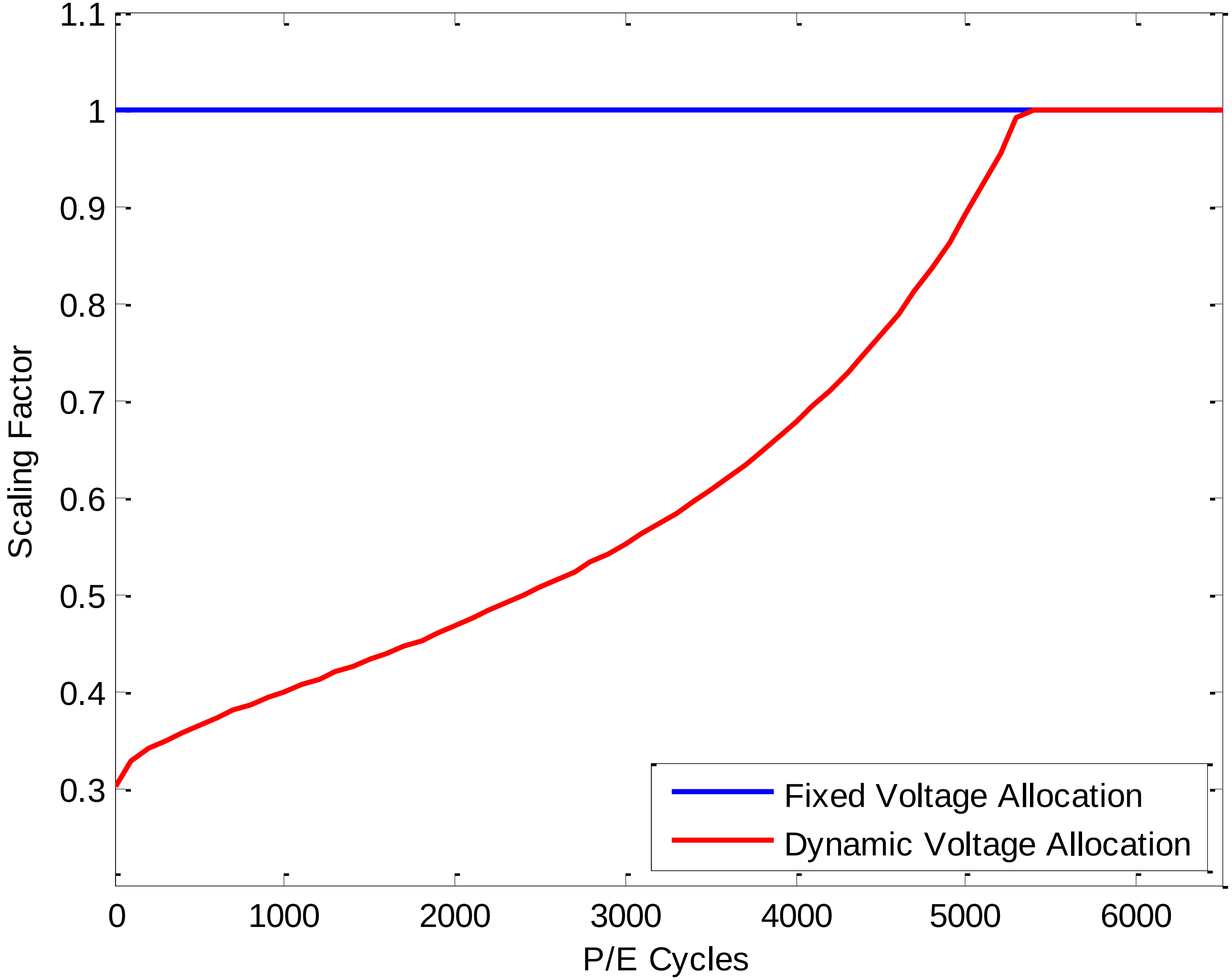
Dynamic Voltage Allocation Scaling Factor Example



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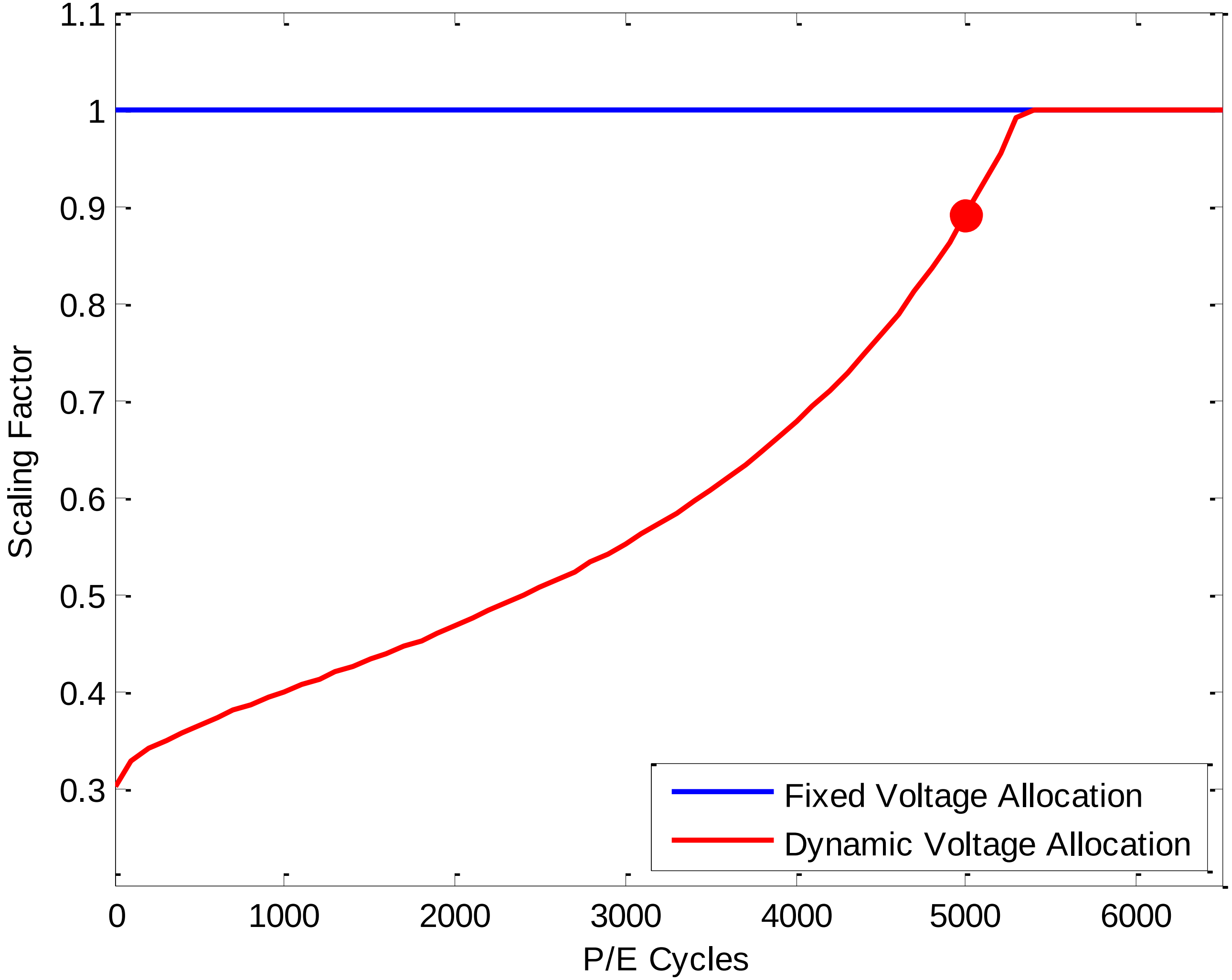
Dynamic Voltage Allocation Scaling Factor Example



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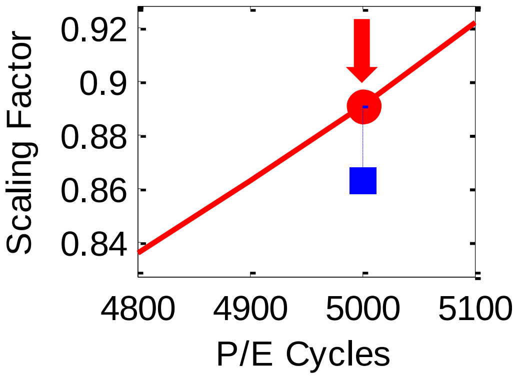
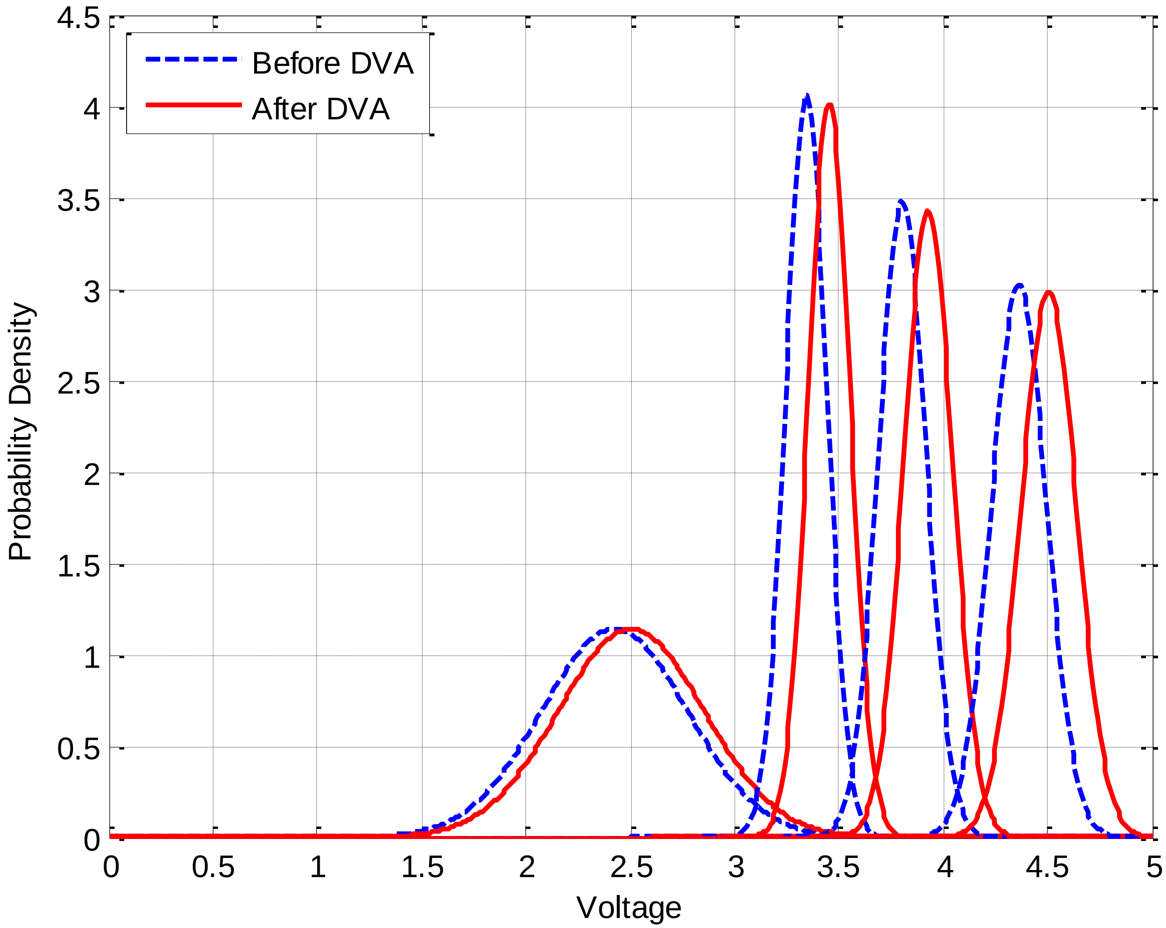
Dynamic Voltage Allocation Scaling Example (P/E = 5000)





1.905 bits --> 1.935 bits

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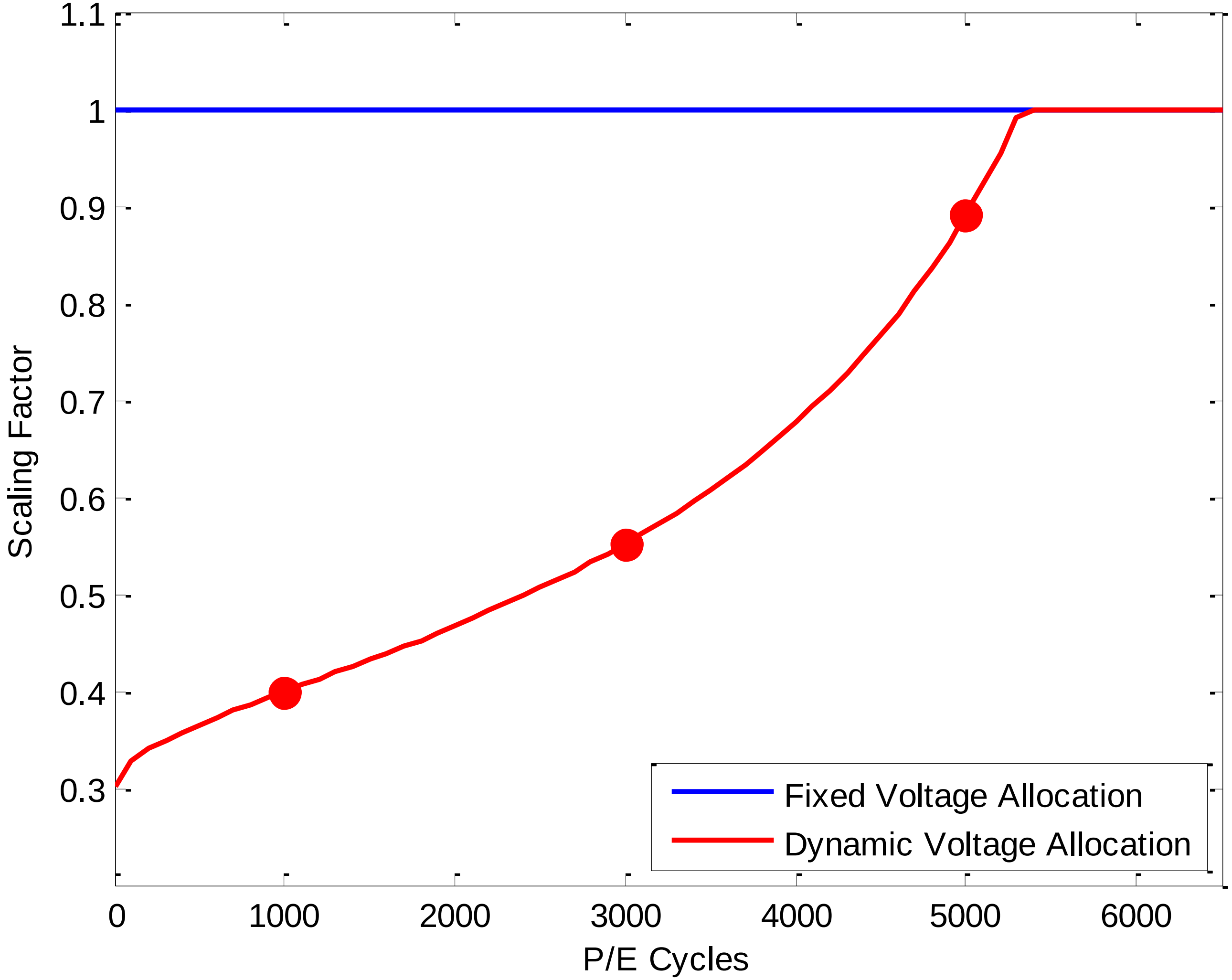
Dynamic Voltage Allocation Scaling Factor Example



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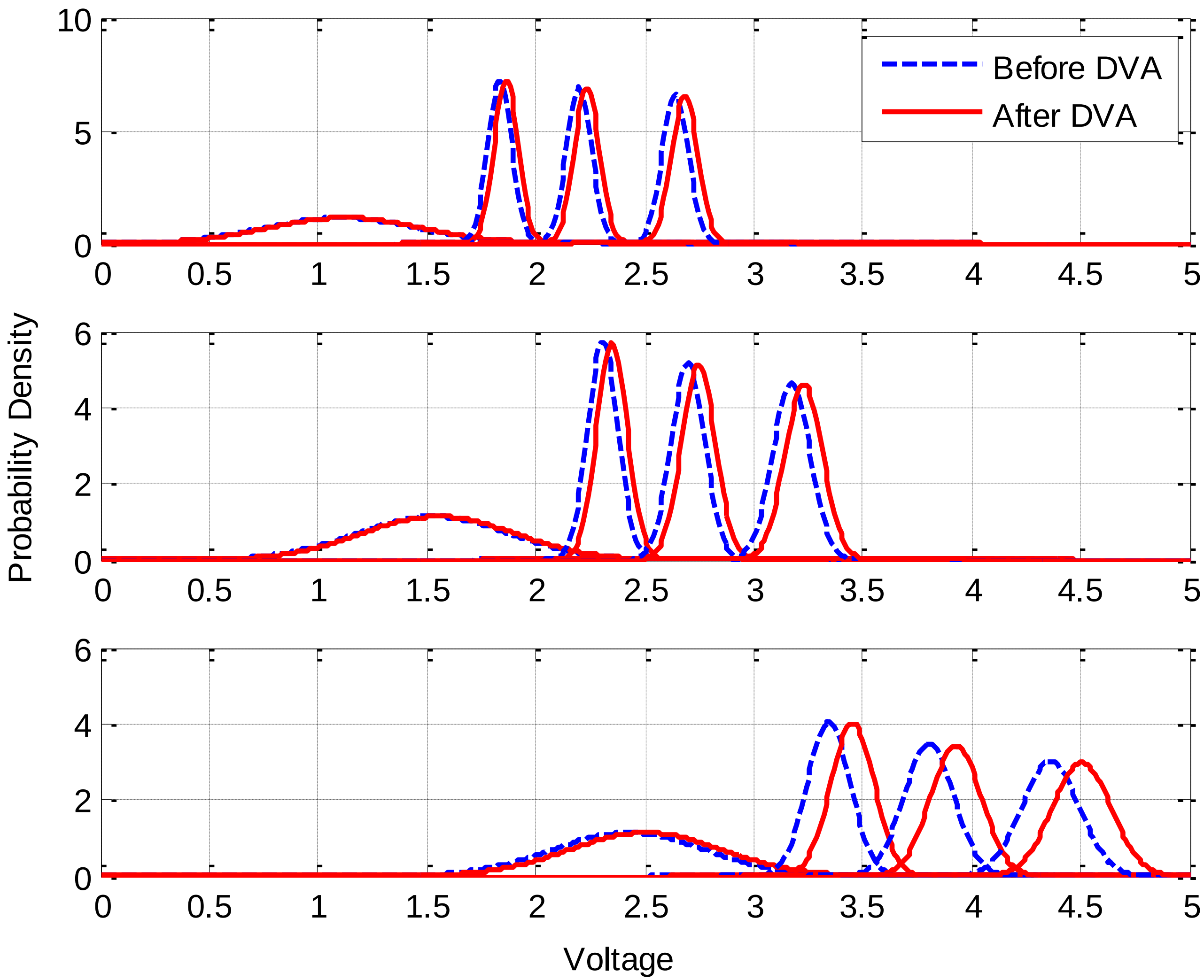
Dynamic Voltage Allocation Scaling Example



P/E = 1000
1.930 bits --> 1.935 bits

P/E = 3000
1.926 bits --> 1.935 bits

P/E = 5000
1.905 bits --> 1.935 bits

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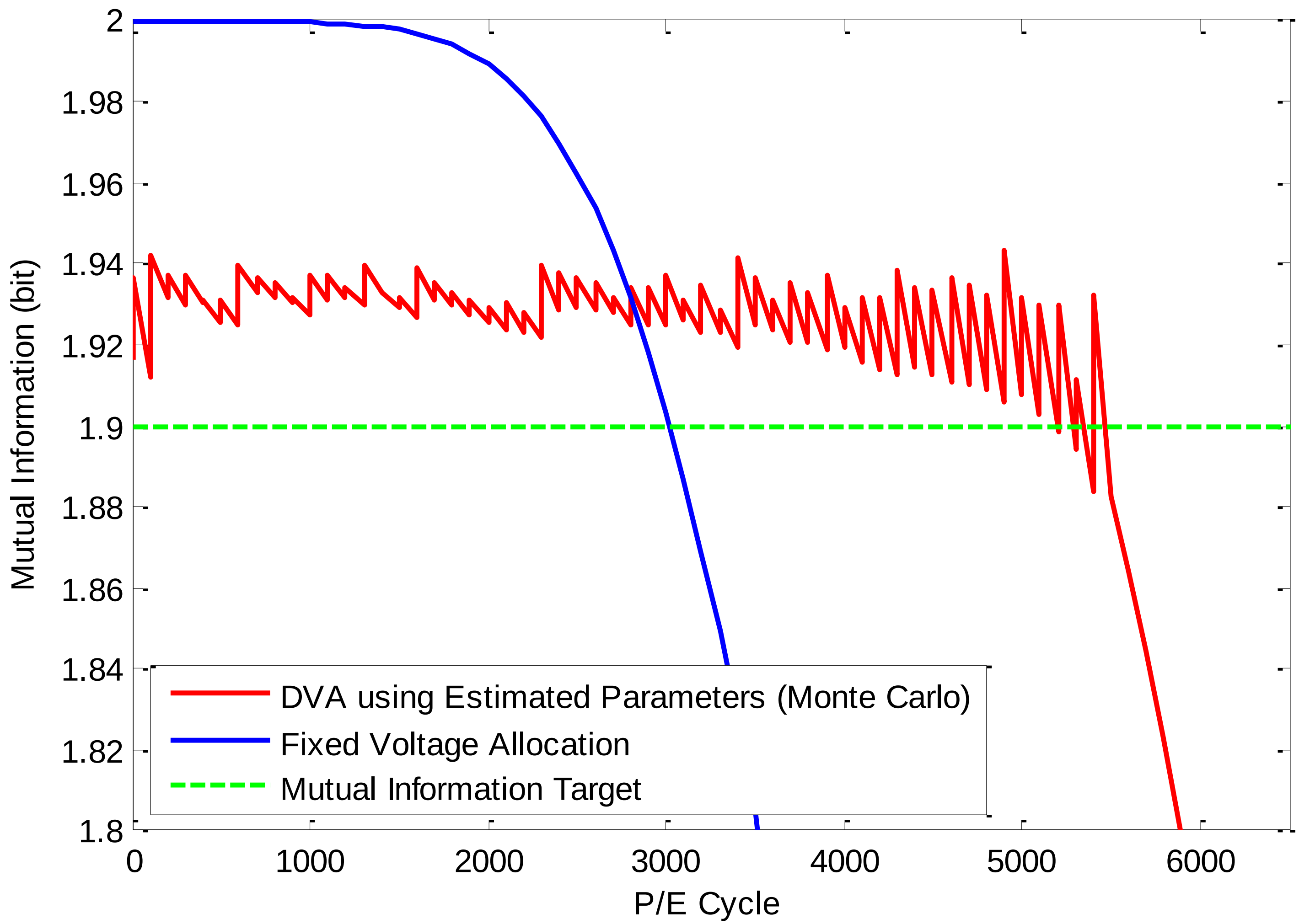
Monte Carlo Simulation Result for MLC Flash



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Conclusion

- Levenberg-Marquardt algorithm can provide accurate channel parameter estimations using limited resolution histograms.

- 10-bin equal-probability binning strategy is a good choice for Flash channel estimation using least squares algorithms.

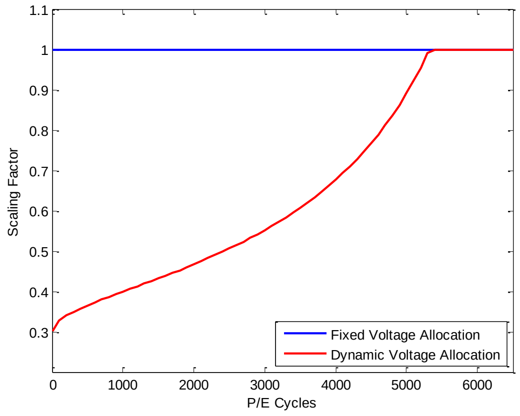
- Dynamic voltage allocation with histogram-based Flash channel estimation can extend lifetime significantly.

Challenges

- Flash can only place write voltage at certain positions.
  - Have results showing the impact is limited.

Challenges

- Flash can only place write voltage at certain positions.
  – Have results showing the impact is limited.
- Impractical to estimate the channel on the fly. & Parameter difference between chips.
  – Estimate offline. We only need a scaling curve guaranteeing the worst case error rate.
  – Machine learning.



Thank you!

Characterize the Peeling Process

To calculate $p_l(x)$, we first need to calculate $p_l(x|i,\omega)$, where i is the initial left degree of a randomly selected edge from B, and ω is the initial erasure state of its incident left node. If $\omega > i-1$, $p_l(x|i,\omega) = 1$ because even if all the neighboring edges of the selected edge provide increments, the VL decoder corresponding to the incident left cannot decode. If $\omega = i-1$, $p_l(x|i,\omega) = 1-(1-x)^{\omega}$, where $1-x$ is the probability that an edge is in the set $\{Q_1,\cdots,Q_t\}$ and the corresponding VL decoder requires all ω increments to successfully decode. If $\omega < i-1$,

$$p_l(x|i,\omega) = \sum_{j=0}^{\omega-1} \binom{i-1}{j} (1-x)^j x^{i-1-j} \ . \qquad (1)$$

Combine the three scenarios,

$$p_l(x|i,\omega) = \sum_{j=0}^{\min(\omega,i)-1} \binom{i-1}{j} (1-x)^j x^{i-1-j} \ , \qquad (2)$$

and when $\omega = 0$, $p_l(x|i,\omega) = 0$.

Summing over all possible combinations of initial left degree i and initial erasure state ω regarding an edge in B,

$$p_l(x) = \sum_{\omega=0}^{m} \delta_\omega \sum_{i=1}^{d_L} \lambda_i p_l(x|i,\omega) \qquad (3)$$

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Characterize the Peeling Process

For a specified edge, define the right neighboring edges of an edge as the *other* edges connected to its incident right node. An edge can be right-degree-one only when all of its right neighboring edges in the original graph B have been removed because they are incident to a left node corresponding to a VL decoder that has already successfully decoded. For each such right neighboring edge, the probability that the left node corresponds to a VL decoder that has already successfully decoded is $1-p_l(x)$. Thus the probability that all $i-1$ right neighboring edges have left nodes corresponding to a VL decoder that has already successfully decoded is $p_r(x|i) = (1-p_l(x))^{i-1}$. Summing over all possible initial right degrees, we have

$$p_r(x) = \sum_{i=1}^{d_R} \rho_i (1-p_l(x))^{i-1} = \rho((1-p_l(x)) \ . \qquad (7)$$

Which adjacent degrees to choose?

- For the inter-frame LDGM code,

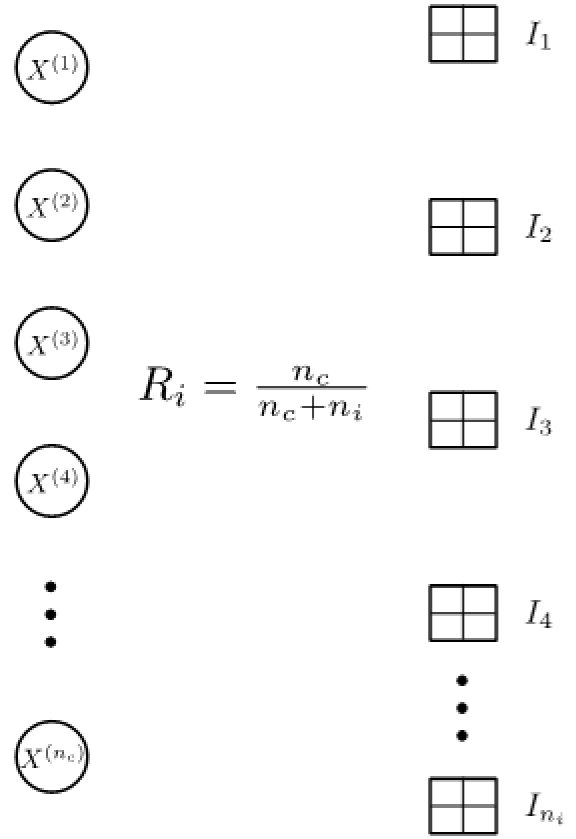
$$\beta_{FF} = \frac{n_i}{n_c} = \frac{1}{R_i} - 1$$

- For any $\lambda(x)$,$\rho(x)$,

$$\beta_{FF} = \frac{\int_0^1 \rho(x)\,dx}{\int_0^1 \lambda(x)\,dx} \geq \beta_{FB}$$

- When $\lambda(x) = x^3$,

$$4\int_0^1 \rho(x)\,dx \geq \beta_{FB}$$



Programming Noise (n_p)

- The uncertainty of the programmed threshold voltage immediately after program operation can be modeled by a Gaussian random variable.

- The variance of the programmed threshold voltage is larger when left in the erased state than when actively programmed.

$$f(n_p) = \begin{cases} N(0, \sigma_e^2) & \text{if } x = 0 \\ N(0, \sigma_p^2) & \text{if } x > 0 \end{cases} \quad \text{where } \sigma_e > \sigma_p$$

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Wear-out Noise (n_w)

- Wear-out induces threshold voltage shift as a result of traps generation and electron trapping/de-trapping during P/E cycling. The number of traps grows as the number of program/erase cycles increases.
- Trap behavior is modeled as random telegraph noise (RTN). This causes the distribution of measured thresholds features exponential tails.
- In some devices, the positive-shift tail is more significant than the negative-shift one, so we use an exponential distribution to model wear-out noise.

$$f(n_w) = \begin{cases} \frac{1}{\lambda} e^{-\frac{n_w}{\lambda}} & n_w \geq 0 \\ 0 & n_w < 0 \end{cases}$$

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Retention Noise (n_r)

- Retention loss is the reduction of programmed threshold voltage over time caused primarily by electron de-trapping.

- Retention noise is modeled as a Gaussian random variable where the mean and variance depend on the retention time and number of traps.

$$f(n_r) = \frac{1}{\sigma_r\sqrt{2\pi}} e^{-\frac{(n_r-\mu_r)^2}{2\sigma_r^2}}$$

Parameter Degradation Model

- Degradation Model
  - Wear-out noise:

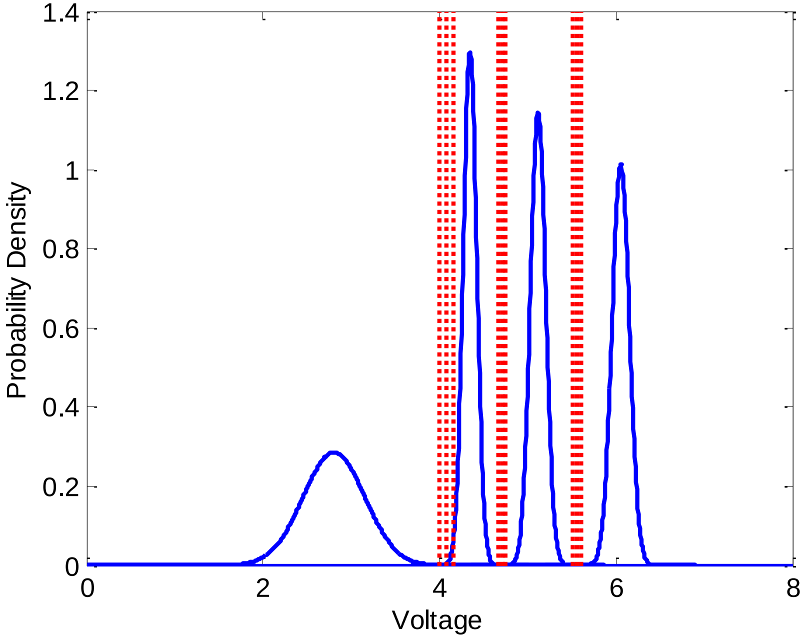
$$\lambda = C_w + A_w \cdot \left(\frac{V_{acc}}{V_{\max}} \right)^{0.62}$$

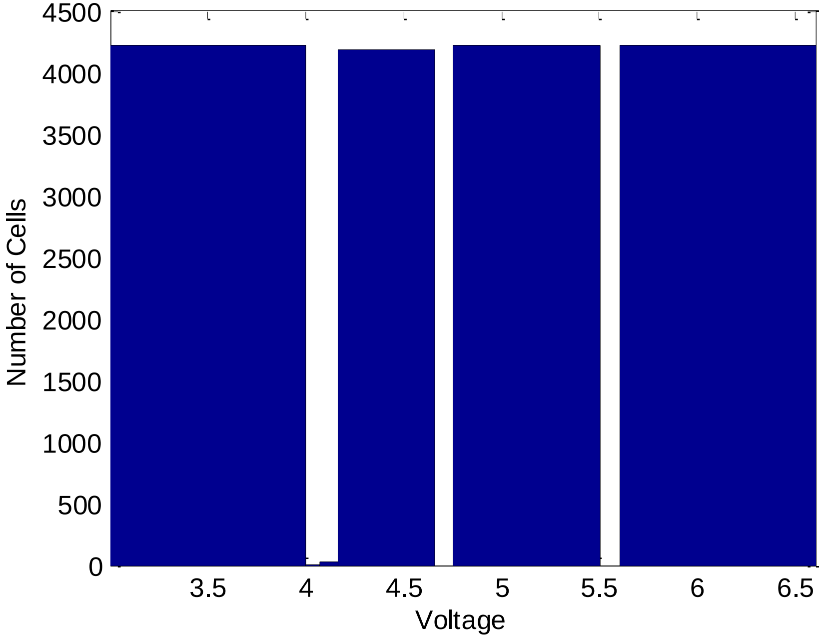
  - Retention noise:

$$\mu_r = -x \cdot \ln\left(1 + \frac{t}{t_0}\right) \cdot \left[A_r \cdot \left(\frac{V_{acc}}{V_{\max}} \right)^{0.62} + B_r \cdot \left(\frac{V_{acc}}{V_{\max}} \right)^{0.3} \right]$$

$$\sigma_r^2 = 0.1x \cdot \ln\left(1 + \frac{t}{t_0}\right) \cdot \left[A_r \cdot \left(\frac{V_{acc}}{V_{\max}} \right)^{0.62} + B_r \cdot \left(\frac{V_{acc}}{V_{\max}} \right)^{0.3} \right]^2$$

MMI Histogram only provides resolution at decision boundaries.





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