Fundamental bounds for power consumption at the physical layer: "waterslide curves" and the price of certainty

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based on joint work with student
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Shannon tells us:

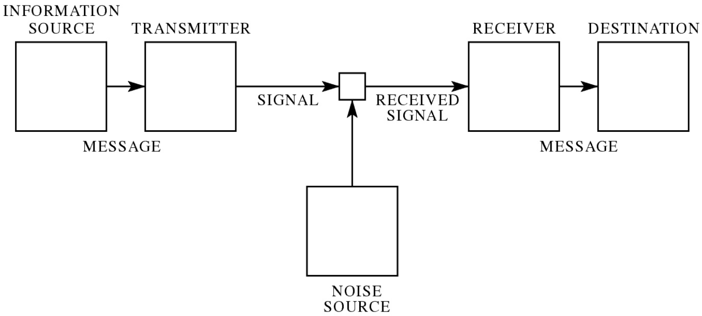

Fig. 1 — Schematic diagram of a general communication system.

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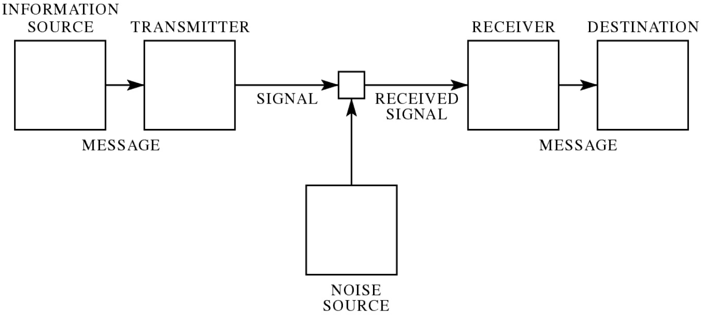

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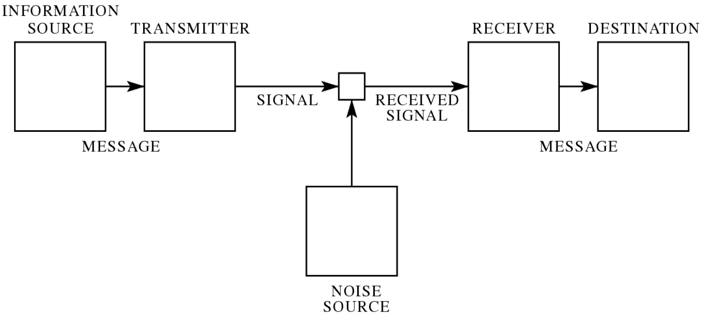
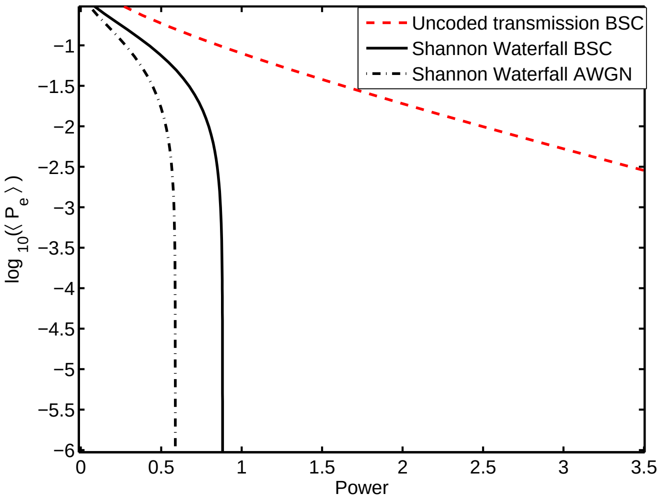


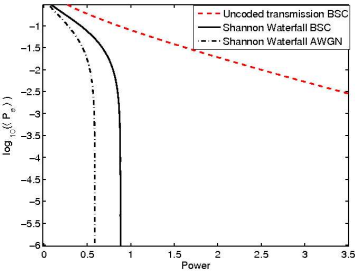
Fig. 1 — Schematic diagram of a general communication system.

- Delay: needed for laws of large numbers to apply
- Power: needed to apply the laws of large numbers

The promise of the waterfall curve



The new problem



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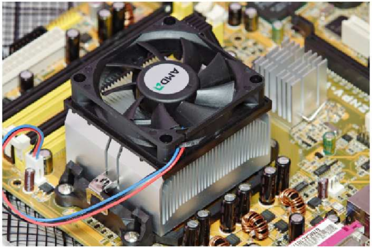

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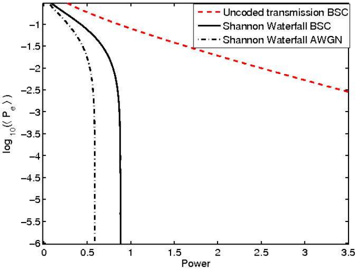

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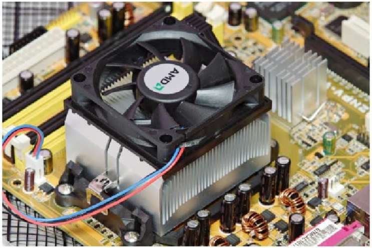

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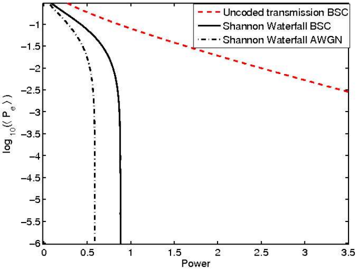

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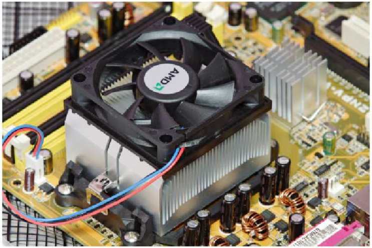

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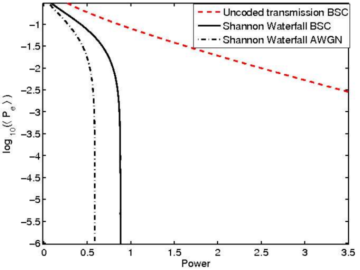

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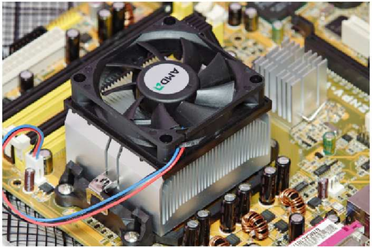

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- New twist: minimize **total power consumption**
- Important technology trends
  - "Moore's law" allows billions of transistors, and but only mildly reduces power-consumption per transistor.
  - New short-range applications: in-home networks, dense meshes, personal-area networks, UWB, between-chip communication, on-chip communication, etc.

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- *Bhardwaj and Chandrakasan*, Allerton 2007
  - Focus on receiver sampling cost in UWB
  - Found lower-rates and adaptive sampling is better

Outline

1. Motivation and introduction
2. Classical results revisited
3. A model for decoder power consumption
4. General lower bounds
5. Asymptotic behavior near capacity
6. Optimal choice of rate

What should capacity-achieving mean?

$$\min \xi_T P_T + \xi_C P_C + \xi_D P_D$$

- ξ_T: net path loss (e.g.$\approx$ 86dB for short-range)
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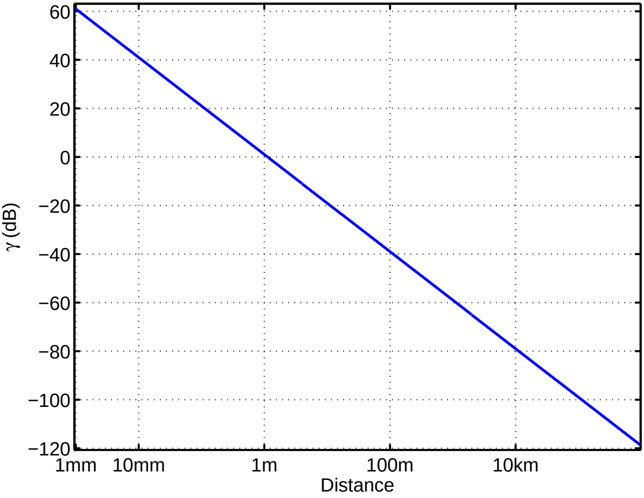
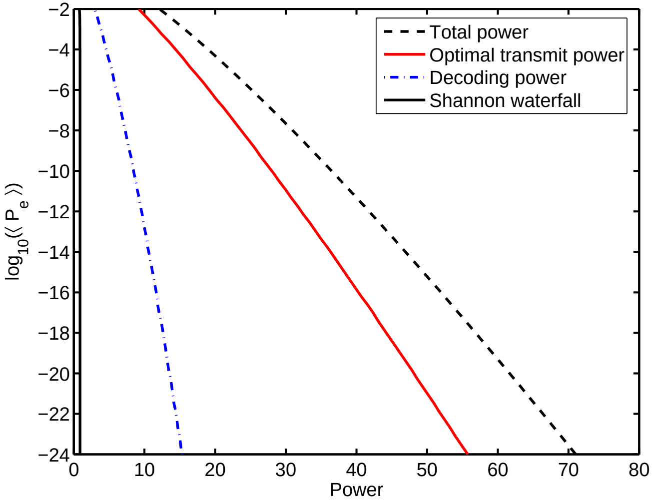
  - $P_T \to C^{-1}(R)$: *capacity achieving*.

Decoding power vs communication range

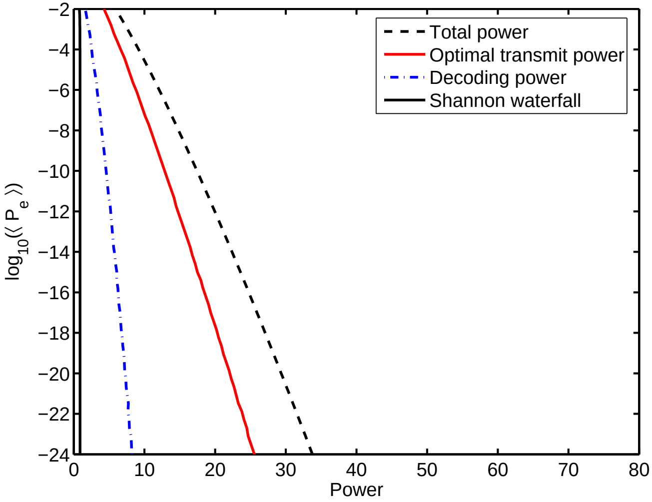


Dense linear codes with brute-force decoding



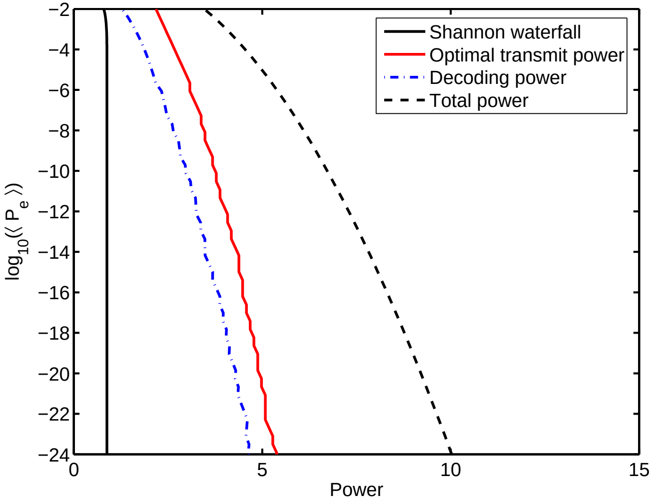
Decoding Power $nR2^{nR}$, Error Prob $2^{-E_{sp}(R,P)n}$

Convolutional codes with Viterbi decoding



Decoding Power $L_c R 2^{L_c R}$, Error Prob $2^{-E_{conv}(R,P)L_c}$

Convolutional with "magical" sequential decoding



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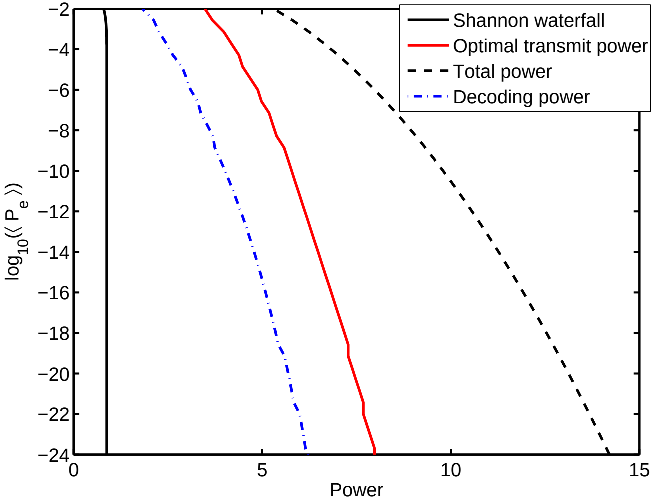
Dense linear codes with "magical" syndrome decoding



Decoding Power $(1-R)nR$, Error Prob $2^{-E_{sp}(R,P)n}$

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- Make assumptions about the decoder rather than the code.

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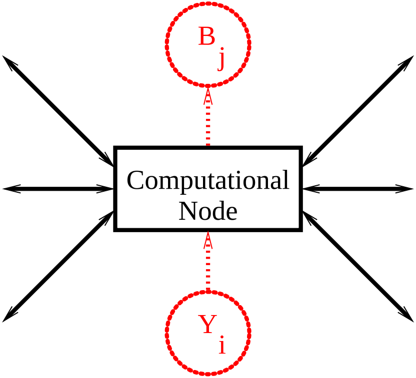

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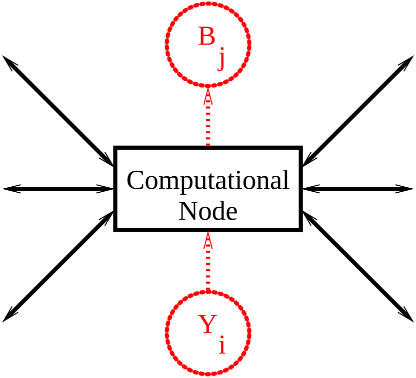

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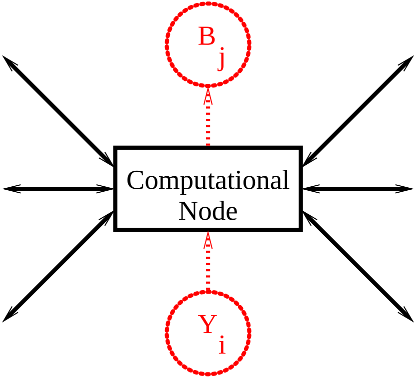

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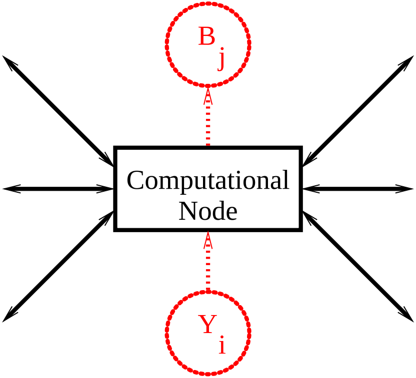

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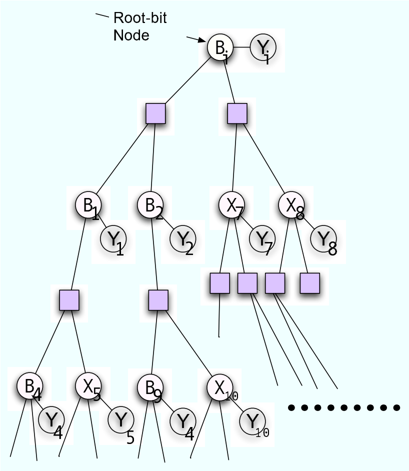
- Rich enough to capture LDPC, RA, Turbo, etc. codes.
- Power-consumption $\geq iE_{node}$ per received sample.

How to lower-bound the number of iterations?



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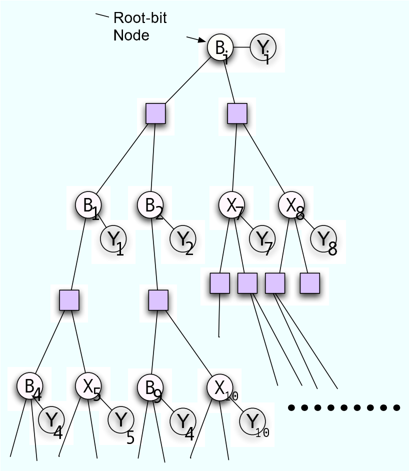

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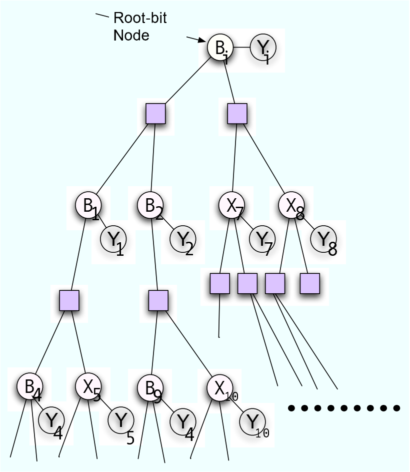

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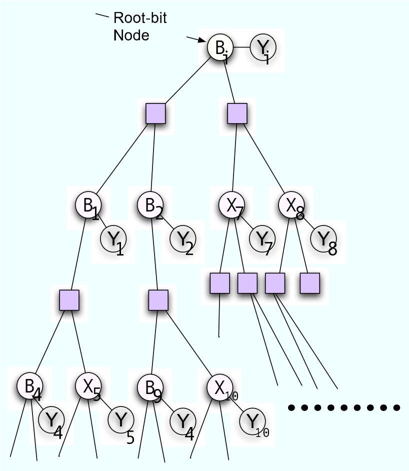

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- Key insight: n is playing a role analogous to delay.

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A **local** "sphere-packing" bound for the AWGN

Decoding neighborhood size $n \le 1 + (\alpha + 1)\alpha^{i-1} \approx \alpha^i$.

$\langle P_e \rangle \ge \sup_{\sigma_G^2 > \sigma_P^2 \mu(n):\ C(G) < R}$

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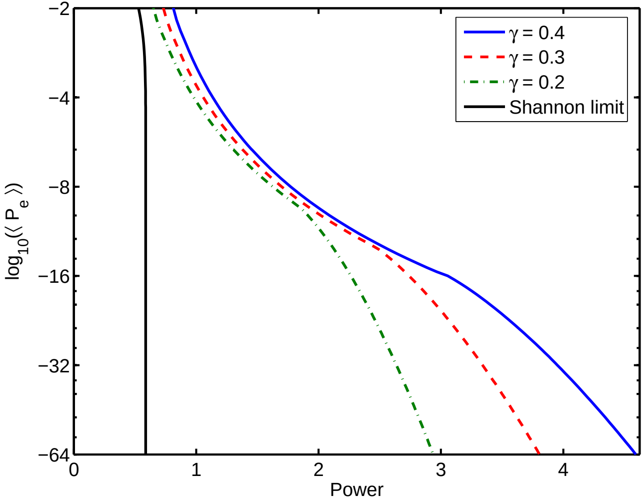
Double-exponential potential return on investments in decoding power!

Waterslide curves for general AWGN case



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- $h_b(p)$: Binary entropy function
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- ϵ: $\sqrt{\frac{1}{K(g)} \log(\frac{2}{h_b^{-1}(\delta(G))})}$
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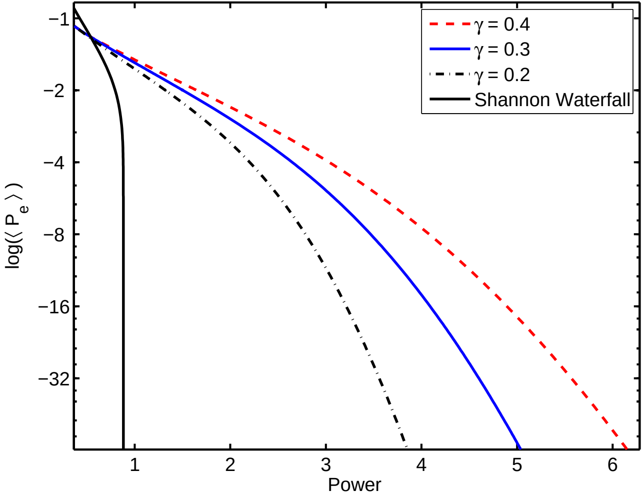
Double-exponential **actual returns** observed by *Lentmaier, et al.* 2005 for regular LDPC codes with iterative decoding!

Detailed look at BPSK case



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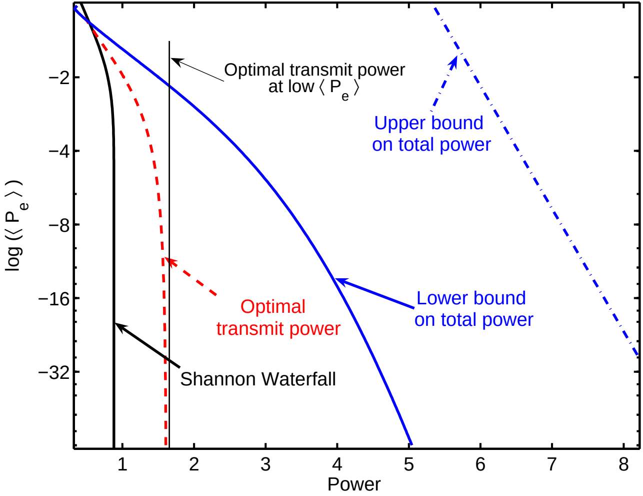
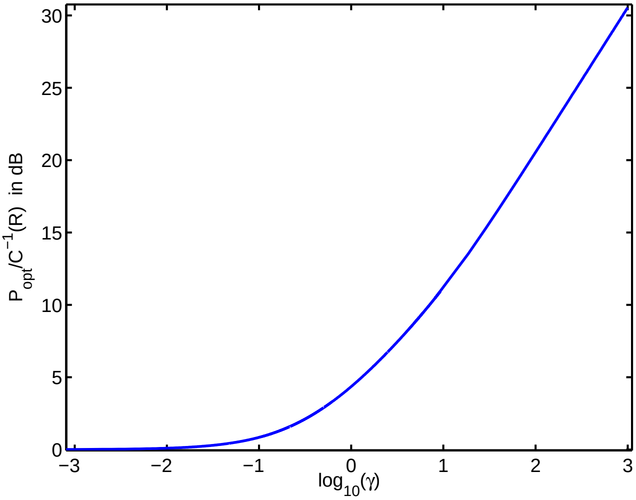


Deviations from Shannon



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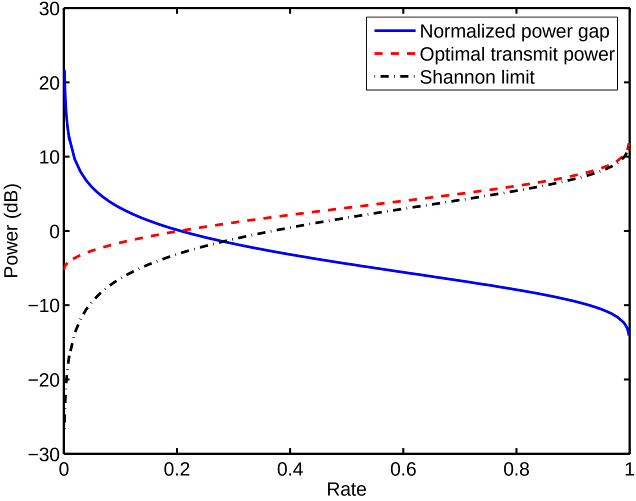

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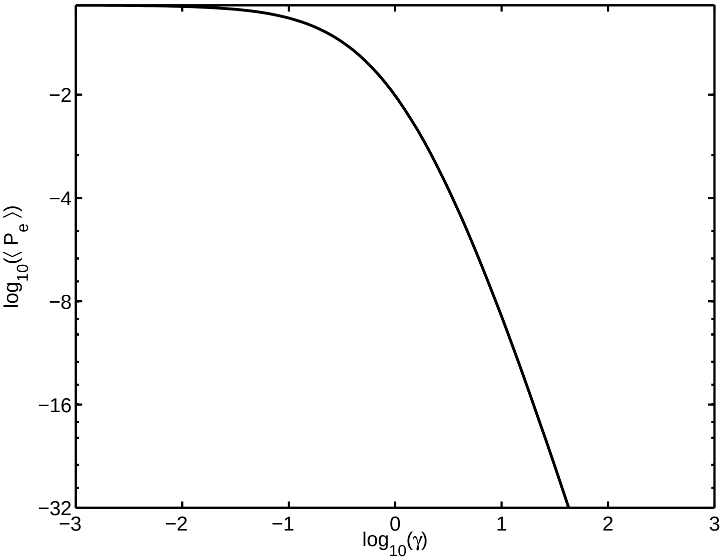

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- ϵ/ϕ assure that the misbehavior is “typical” (*even if n is small*)
- Probability of an error event under P is lower-bounded by a convex-$\cup$ function f of the probability under G.
- Average probability under P is minimized by f of the average probability under G.

The low P_e limit

- Dominant term: $D(G||P)$ term in exponent.
- $P_e \approx \exp(-D(C^{-1}(R)||P)n) = \exp(-D(C^{-1}(R)||P)\alpha^i)$

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- Solved by:

$$f(R,\zeta) / \frac{\partial f(R,\zeta)}{\partial\zeta} = \gamma$$

where $f(R, \frac{P_T}{\sigma_P^2}) = D(C^{-1}(R)||P)$.

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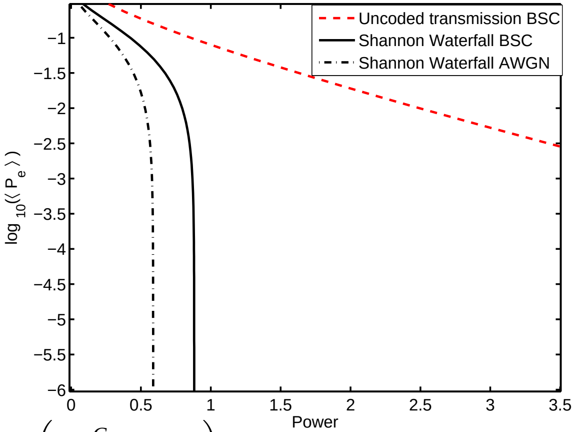
The waterfall curve revisited



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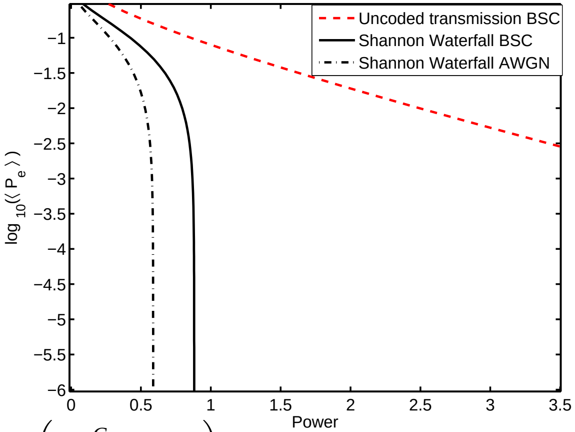

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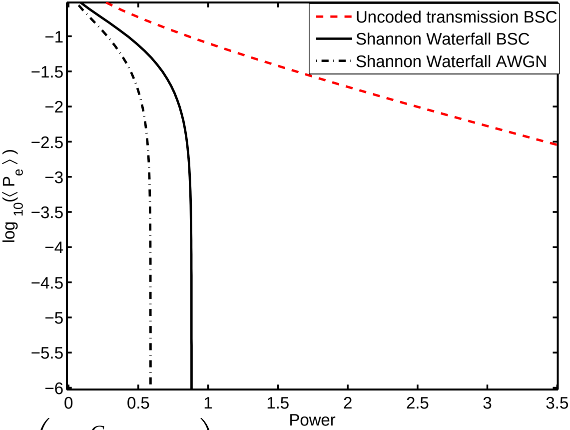

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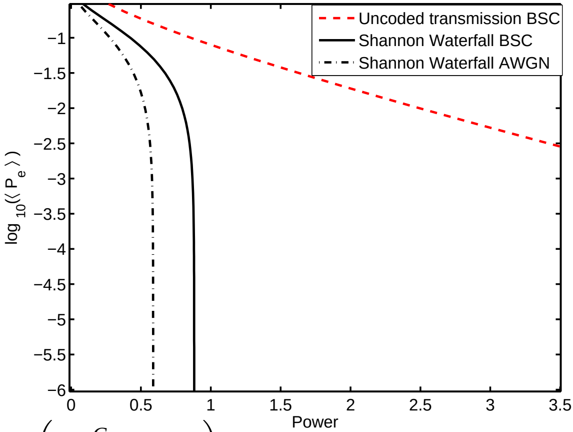
The waterfall curve revisited



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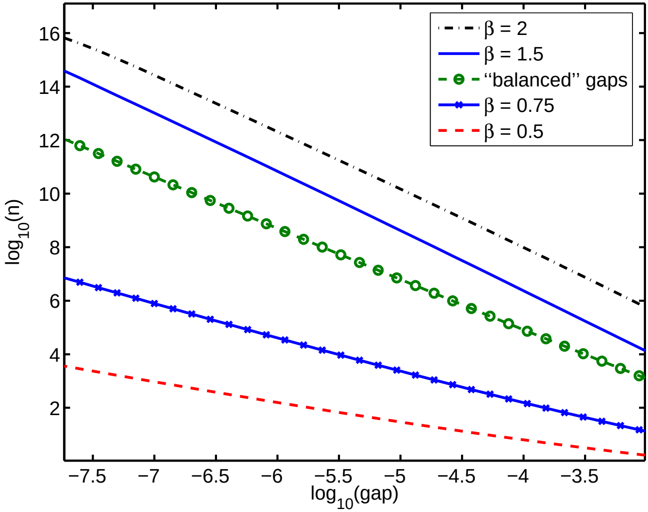
- Pick a joint path to certainty: $P_e = gap^{\beta}$.
- Let $R \to C \ldots$

Zoom into the neighborhood of capacity



Asymptotic scaling of iterations and gap

Assume $P_e = gap^{\beta}$ and BSC channel:

- If $\beta \geq 1$, $i \geq 2 \log \frac{1}{gap} + \log \log \frac{1}{gap} + c_\beta$.
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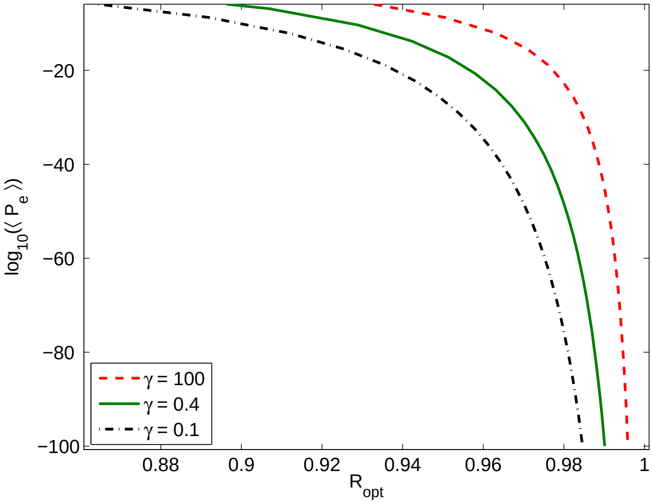
- Optimize over the choice of R as P_e varies.

Results for BPSK signaling



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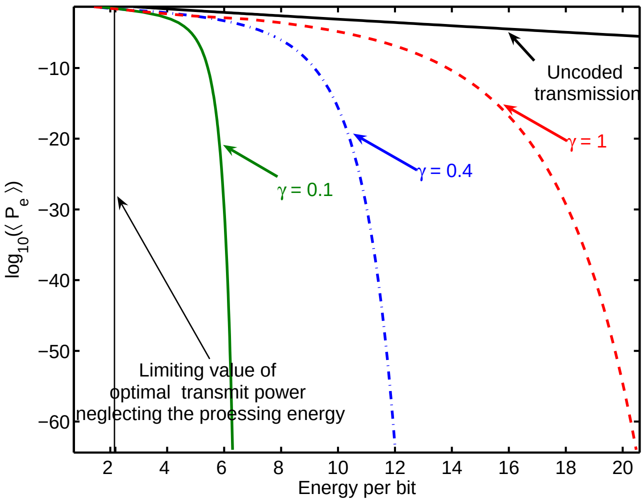

Concluding remarks

More details:
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- Expand scope to cover multiterminal problems and other components.