Investigating a Physically-Based Signal Power Model for Robust Low Power Wireless Link Simulation

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Outline

- Introduction
- Phase correction and signal extrapolation
- Validation and Evaluation
- Conclusion

Low Power Wireless Link Performance Is Poor

- Protocols for sensor networks are carefully designed and heavily simulated
- Packet yield in real deployments is low:
  - Volcano Study: 68% [ESWN 05]
  - Great Duck Island: 58% [SenSys 04]
  - Redwood Study: 40% [SenSys 05]
  - Potato Agriculture Study: 2% [WPDRTS 06]
- Low packet yield leads to loss of information from networks

Wireless Link Simulation

- Analytical Models
  - For example, Path Loss and Shadowing Model [ICEE 06]
  - Many assume packet reception independence
- Empirical Models
  - Packet receptions and losses are not temporally independent
  - Noise+Interference modeled using CPM [IPSN 07]

TOSSIM 2.0.1 (2007)

- Closest Fit Pattern Matching (CPM):
  - (1) Pre-process an experimental noise trace:

0	2	1	2	0	2	2	0	0	1	1	1	1	2	0	0	0	2	9	0

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

k = History size = 2

HyungJune Lee, Alberto Cerpa, and Philip Levis, "Improving Wireless Simulation Through Noise Modeling." In Proceedings of the IPSN, 2007.

  - (2) Take k values from experiment; then sample PMF:

0	2	2			

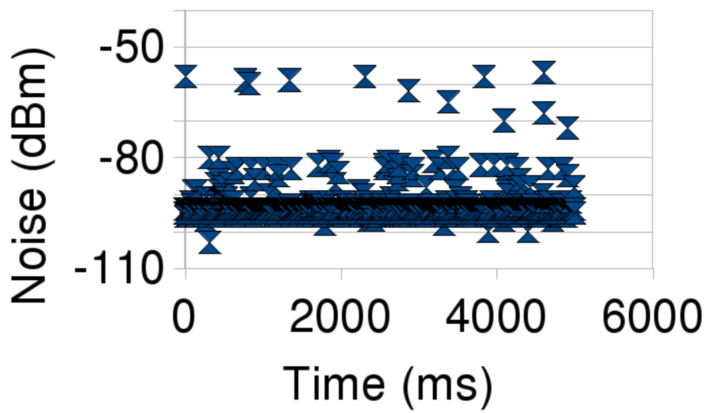
0	2	2	0		

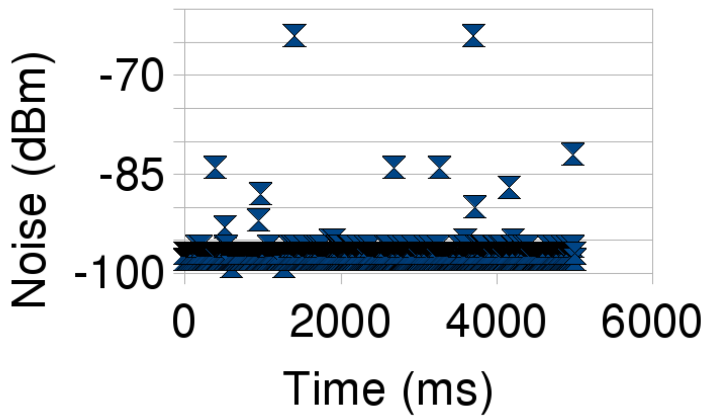
0	2	2	0	0	

- Signal power given by constant link gain value.

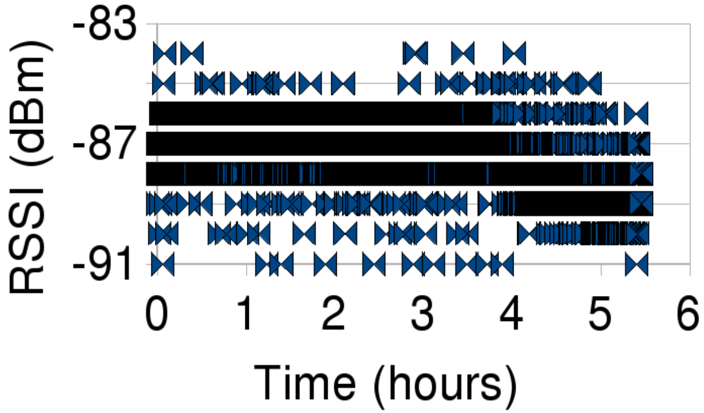
Reasons for Packet Reception Correlation

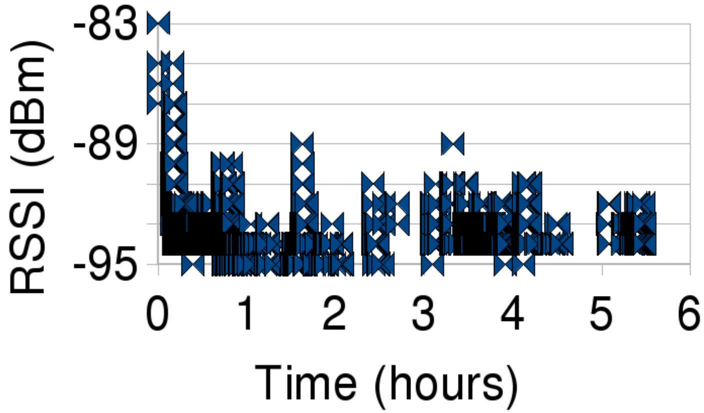
- Noise+Interference in environment is correlated





- Signal Power of successive packets is also correlated





Physically Modeling Signal Power

- **Idea:** Collect a signal power trace and use CPM to model signal power.
- Collecting power traces is more complex than collecting noise traces, since:
  - Signal power is a property of a pair of nodes in the network
  - Signal power can only be approximated by sampling the RSSI register, which actually reports signal+noise, where <u>wave phases</u> are considered
  - If a packet is lost in transmission, then even the RSSI estimate is not possible.

Contributions

- We suggest solutions to major challenges in modeling signal power:
  - Correcting for phase
  - Two algorithms for extrapolating from lossy traces: Average Value and Expected Value

- Our algorithms improve simulation substantially:
  - PRR simulated to within 22% absolute difference
  - Methods reduce KW distance of simulations by 66% compared to current approaches

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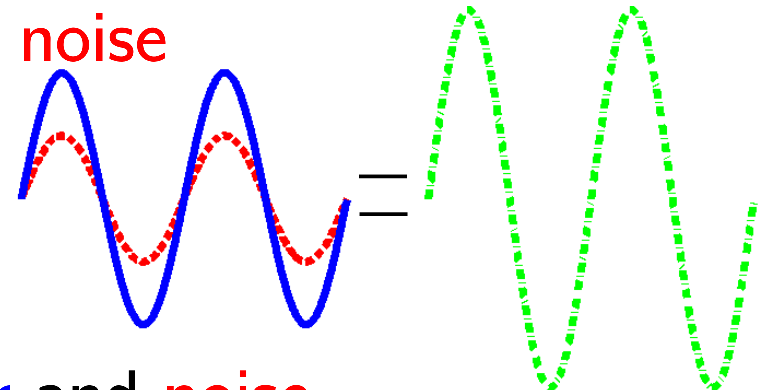
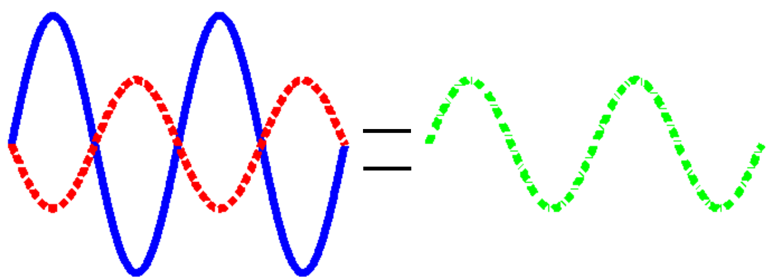
Converting RSSI Readings to Signal Power

- Phase assumption used to correct RSSI reading:
  - In phase signal power and noise



  - Out of phase signal power and noise



  - Neutral phase: assumes net phases cancel out
- These assumptions are simplifications to reality.

Algorithm for Filling-In Lossy Signal Power Links

- Two algorithms suggested:
  - Fill in average value for all missing values
  - Compute expected distribution of missing signal power values over the whole trace and then sample the distribution

Average Value Filling-In Algorithm

Lossy Signal Power (dBm) =

-82	??	??	-87	-85	??	-86	-82	??	-81	??

Average Value Filling-In Algorithm

Lossy Signal Power (dBm) =

-82	??	??	-87	-85	??	-86	-82	??	-81	??

Average Signal Power (Rounded to Integer) (dBm) = -84

Average Value Filling-In Algorithm

Lossy Signal Power (dBm) =

-82	??	??	-87	-85	??	-86	-82	??	-81	??

Average Signal Power (Rounded to Integer) (dBm) = -84

Filled-In Signal Power (dBm) =

-82	-84	-84	-87	-85	-84	-86	-82	-84	-81	-84

Expected Value PMF Filling-In Algorithm

Average Noise (dBm) = -90

Lossy Signal Power (dBm) =

-82	??	??	-87	-85	??	-86	-82	??	-81	??

Expected Value PMF Filling-In Algorithm

Average Noise (dBm) = -90

Lossy Signal Power (dBm) =

-82	??	??	-87	-85	??	-86	-82	??	-81	??

SNR (dB) = 8 3 5 4 8 9

Expected Value PMF Filling-In Algorithm

Average Noise (dBm) = -90

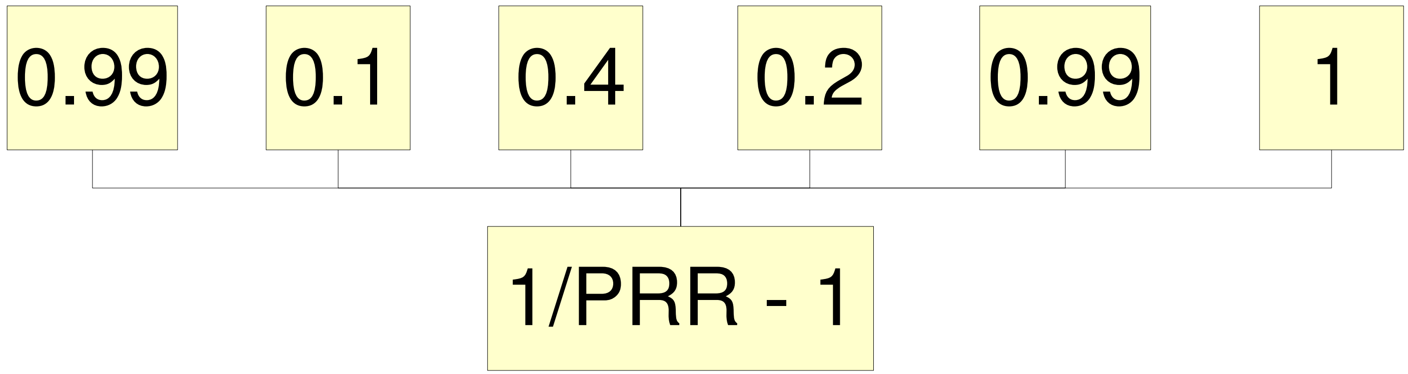
Lossy Signal Power (dBm) =	-82	??	??	-87	-85	??	-86	-82	??	-81	??
SNR (dB) =	8			3	5		4	8		9	
Packet Reception Rate (PRR) =	0.99			0.1	0.4		0.2	0.99		1	

Expected Value PMF Filling-In Algorithm (continued)

Packet Reception Rate (PRR) =	0.99	0.1	0.4	0.2	0.99	1

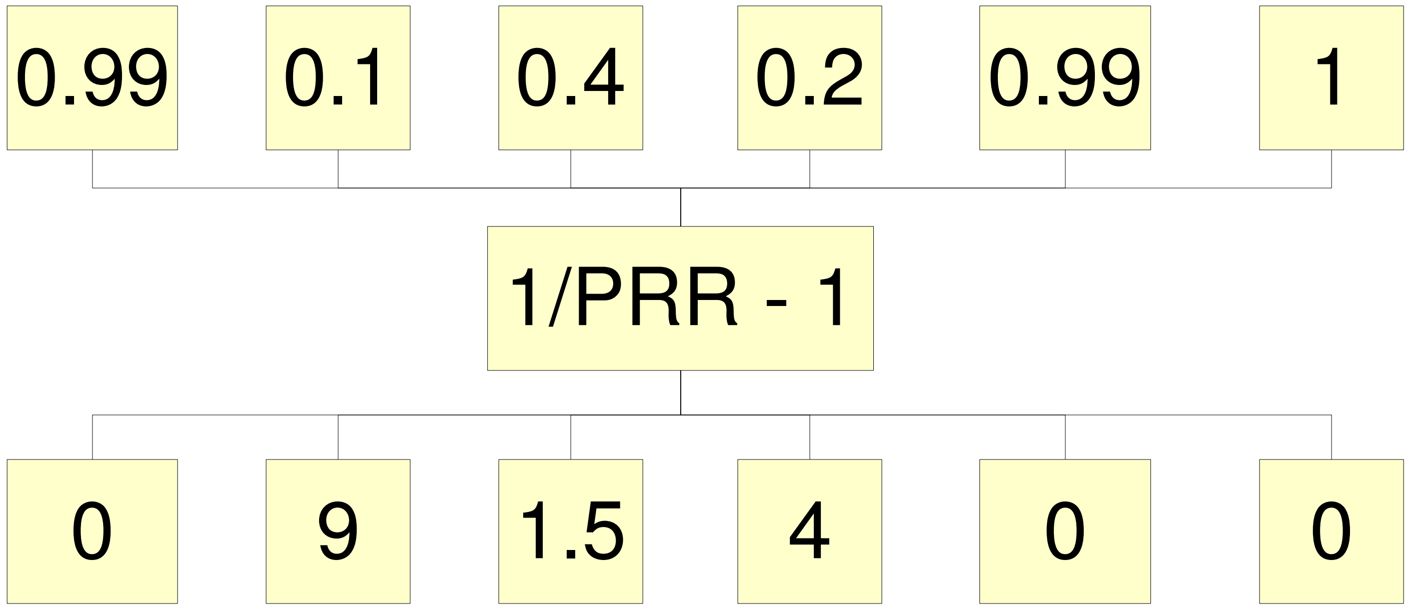
Expected Value PMF Filling-In Algorithm (continued)

Packet Reception Rate (PRR) =



Expected Value PMF Filling-In Algorithm (continued)

Packet Reception Rate (PRR) =



Expected Number of Packets Missed =

Expected Value PMF Filling-In Algorithm (continued)

Packet Reception Rate (PRR) =	0.99	0.1	0.4	0.2	0.99	1

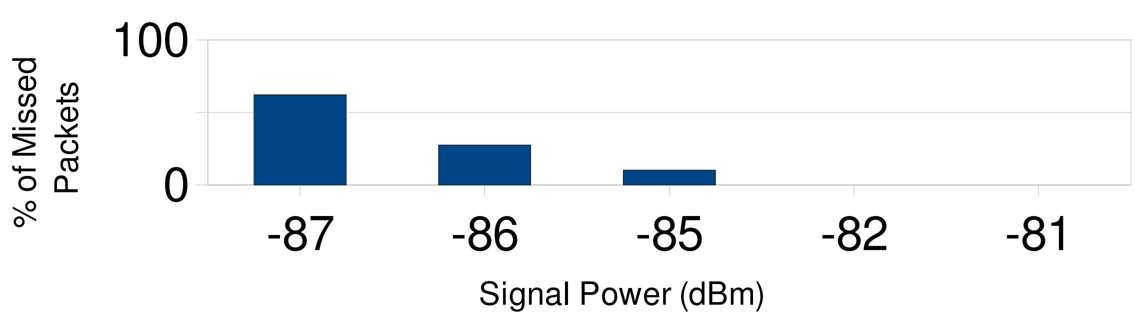
1/PRR - 1

Expected Number of Packets Missed =	0	9	1.5	4	0	0
Signal power values (dBm) =	-82	-87	-85	-86	-82	-81

Expected Value PMF Filling-In Algorithm (continued)

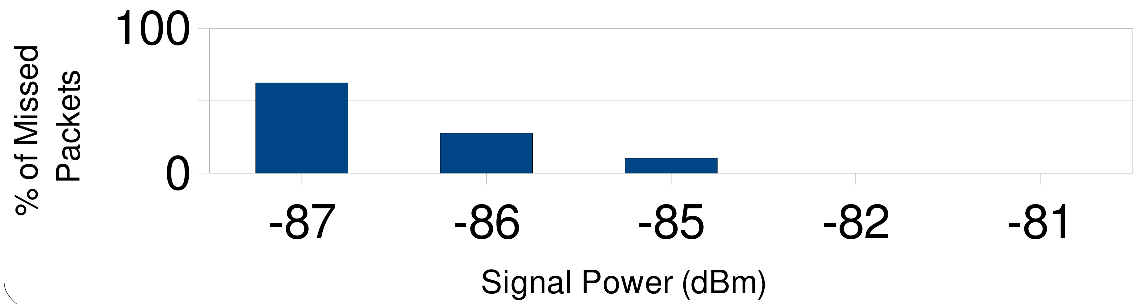
Expected Number of Packets Missed =	0	9	1.5	4	0	0
Signal power values (dBm) =	-82	-87	-85	-86	-82	-81

Expected Packets PMF =



Expected Value PMF Filling-In Algorithm (continued)

Expected Packets PMF =



Filled-In Signal Power (dBm) =

-82	-87	-86	-87	-85	-87	-86	-82	-87	-81	-85

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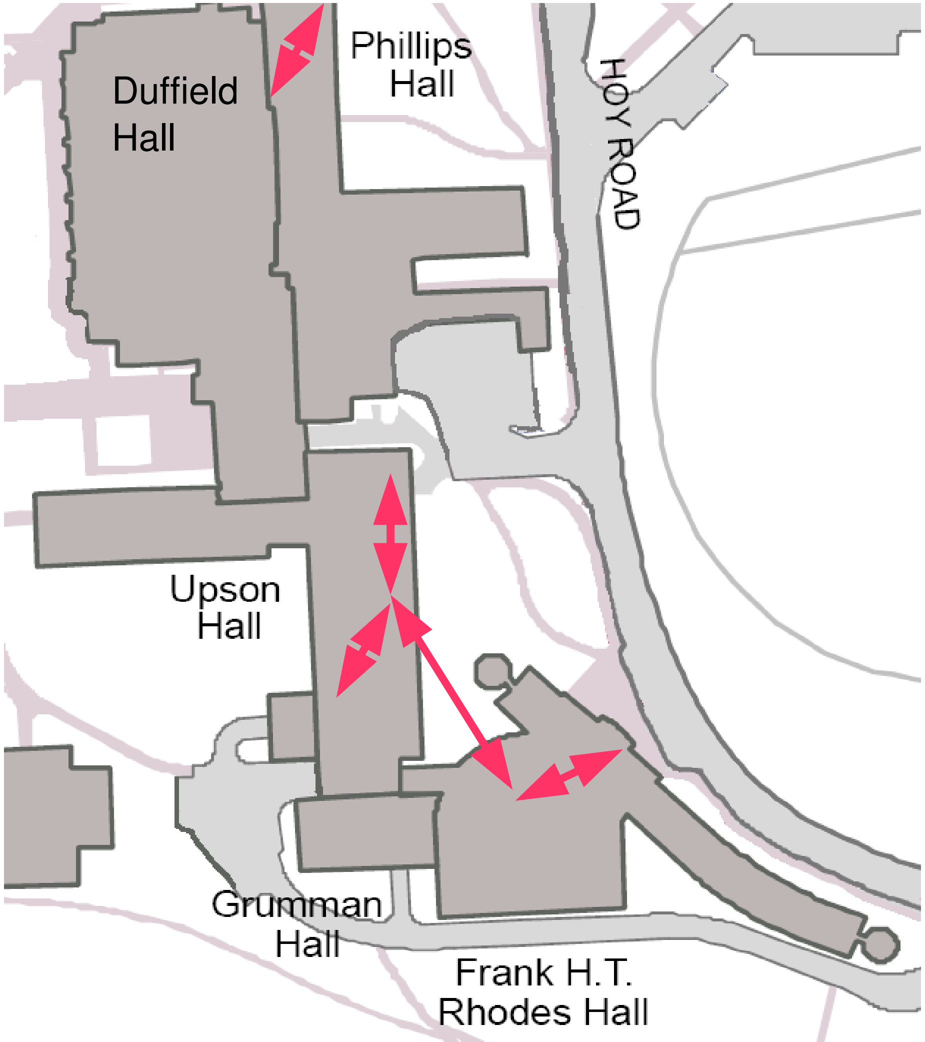
Validation

- Goal is to correctly simulate a particular link between to nodes
- It is possible to use experiments to validate this simulation method

- Conducted packet delivery experiments at 4 Hz for 12 hours at various locations on the Cornell University Campus.
- 4 Hz frequency chosen as a baseline: future work will investigate different collection frequencies and the impacts on the results.

Experiment Locations



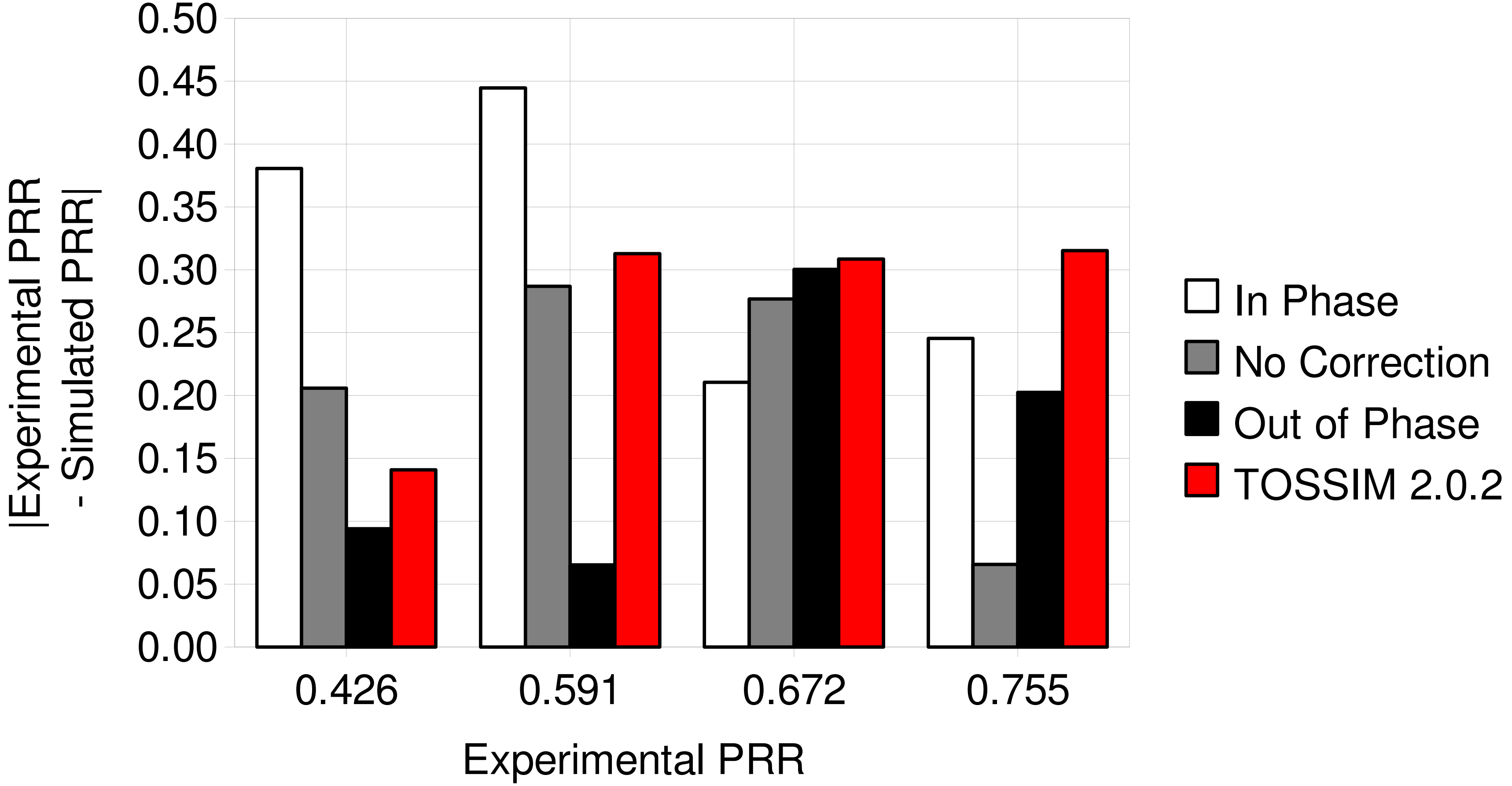
http://www.parking.cornell.edu/pdf/Stu_combo_2006.pdf

Evaluation Criteria

- Packet Reception Rate (PRR)
  - First order parameter, difficult to get right in general wireless simulators
- Kantorovich-Wasserstein (KW) distance on Conditional Packet Delivery Functions (CPDFs)
  - Rigorous measure of the similarity between two distributions, which places more emphasis on rare rather than common case
  - Captures packet burstiness at the level of individual packets.

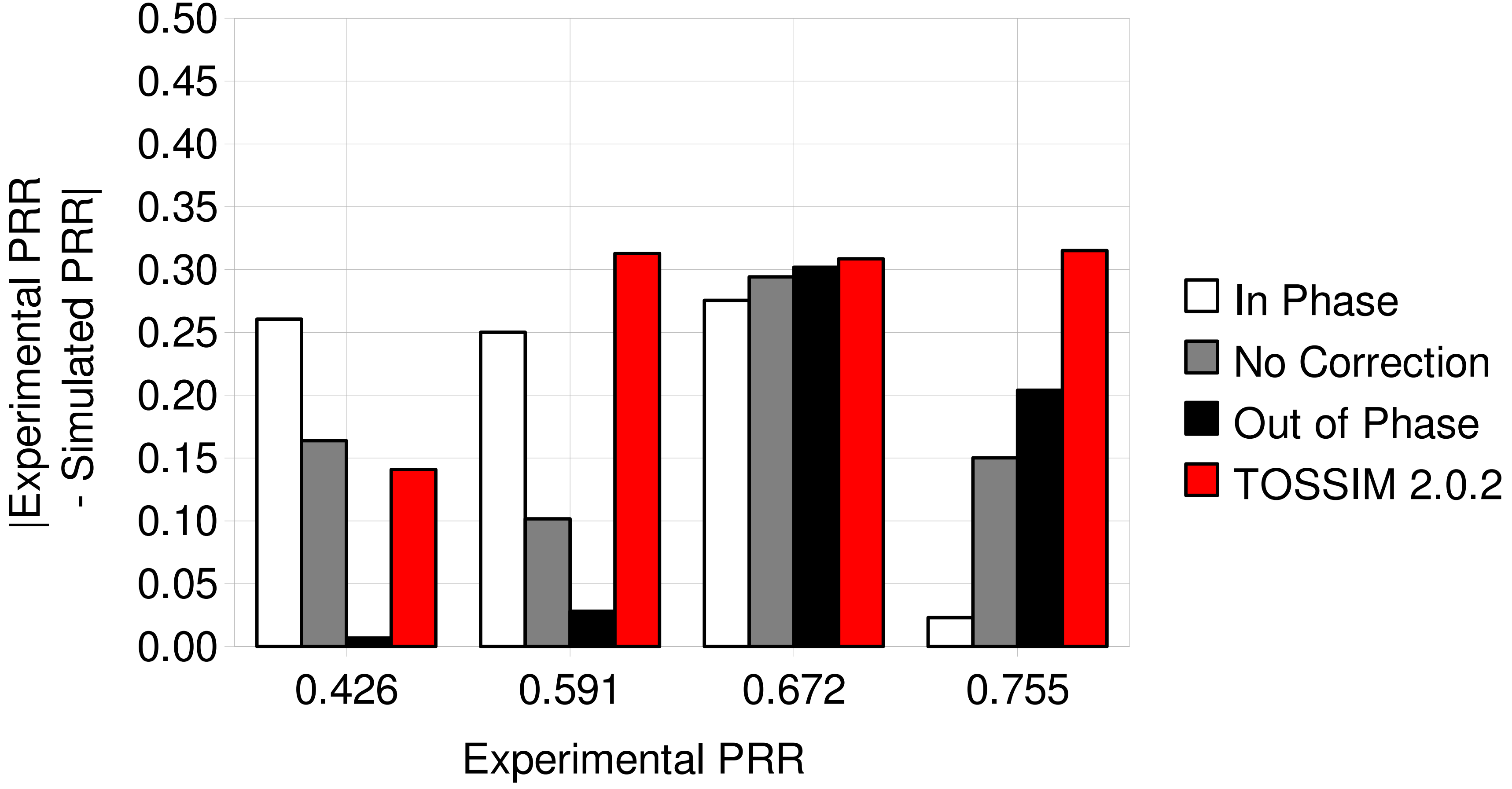
PRR for Expected Value PMF Algorithm

- Maximum absolute error bounded by 22%.



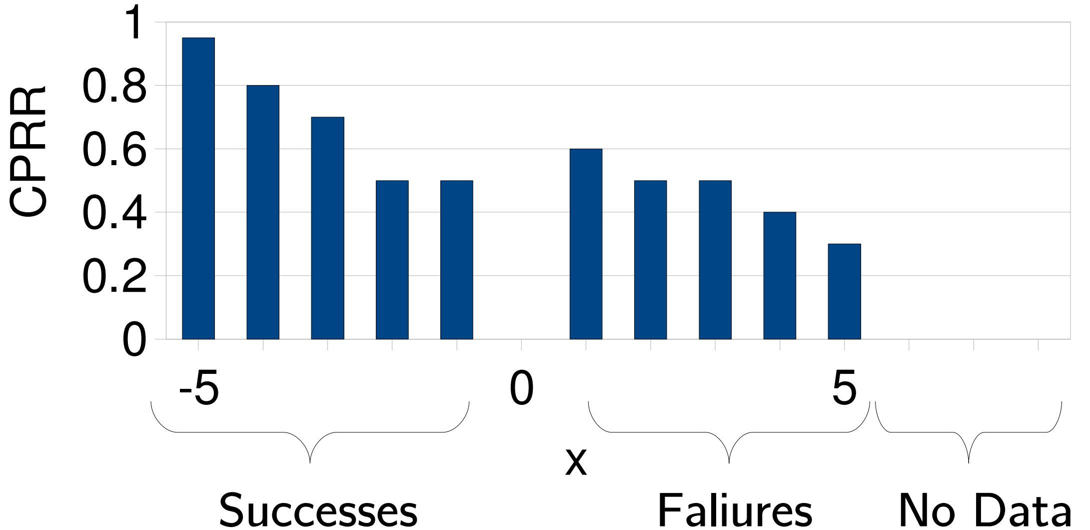
PRR for Average Value Algorithm

- Maximum absolute error bounded by 28%.



Conditional Packet Delivery Function (CPDF)

- Considers the conditional packet reception rate (CPRR) after streams of $|x|$ consecutive receptions for $x < 0$ or x consecutive failures for $x > 0$.

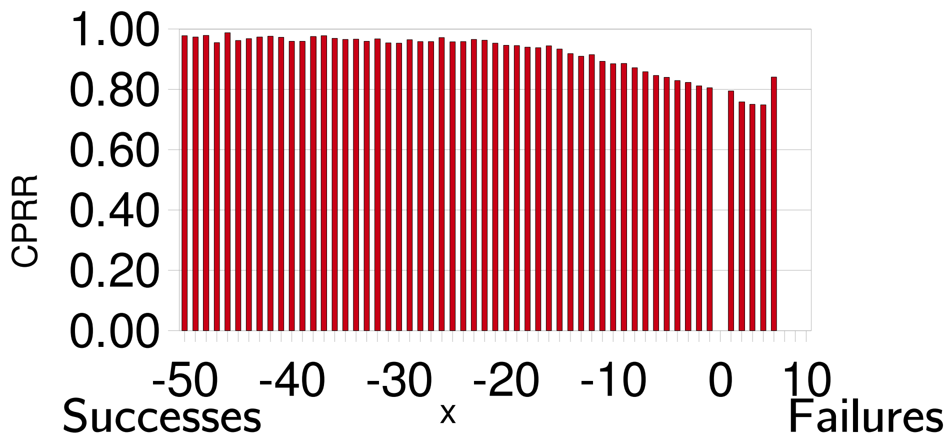


- Kantarovich-Wasserstien Distance measures differences between distributions, including CPDFs.

CPDF: PRR = 82.5%

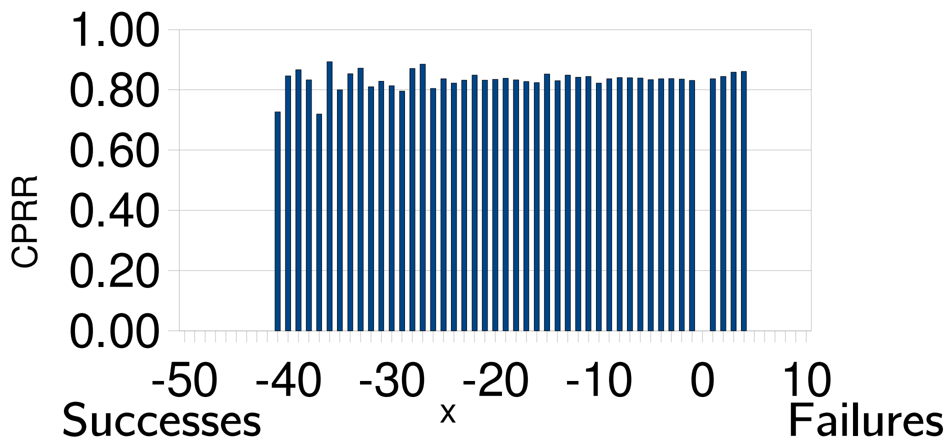
Real Signal

Power



Log Normal

Shadowing Model

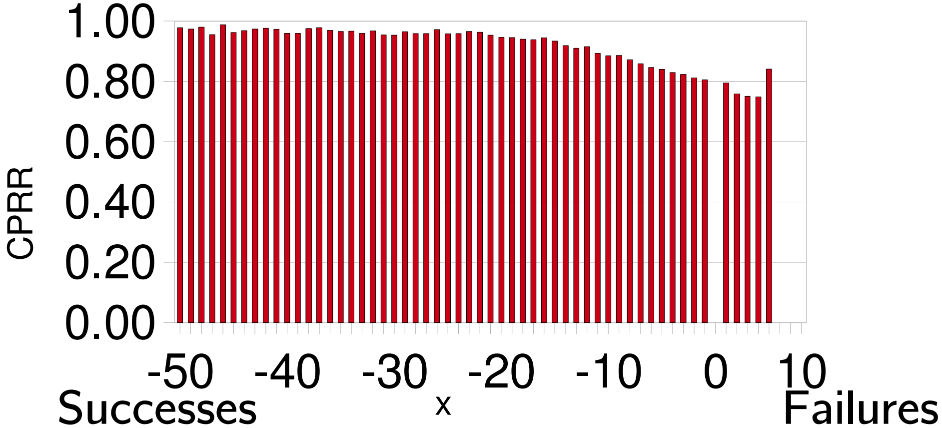


KW Distance = 0.10

CPDF: PRR = 82.5%

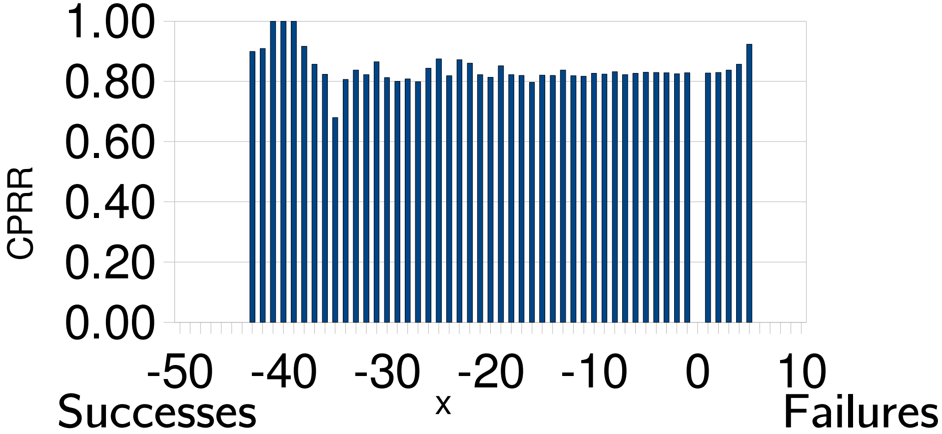
Real Signal

Power



TOSSIM

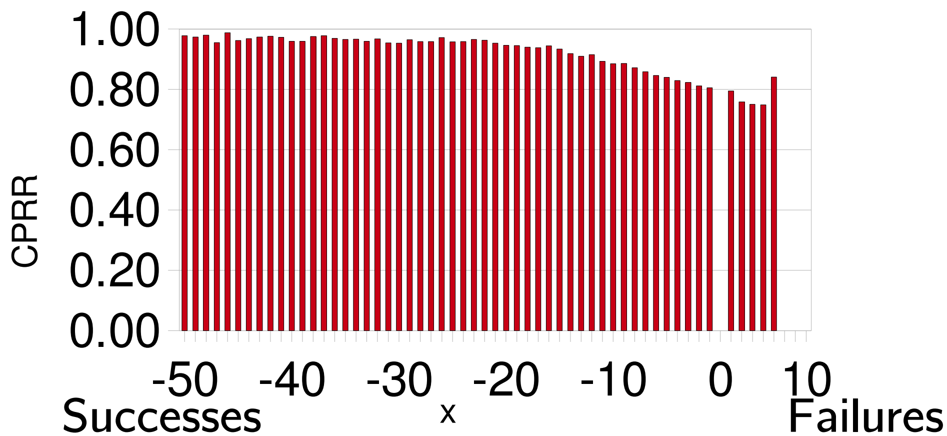
2.0.2



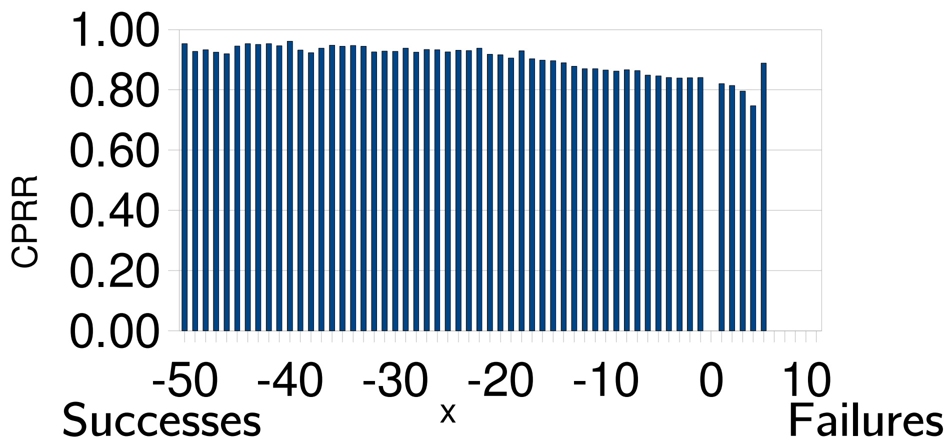
KW Distance = 0.09

CPDF: PRR = 82.5%

Real Signal Power



CPM+Expected Value PMF

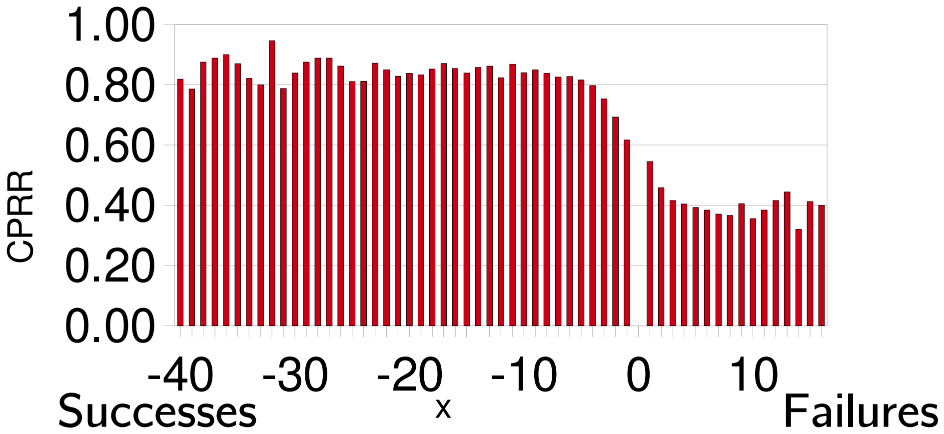


KW Distance = 0.03

CPDF: PRR = 58.5%

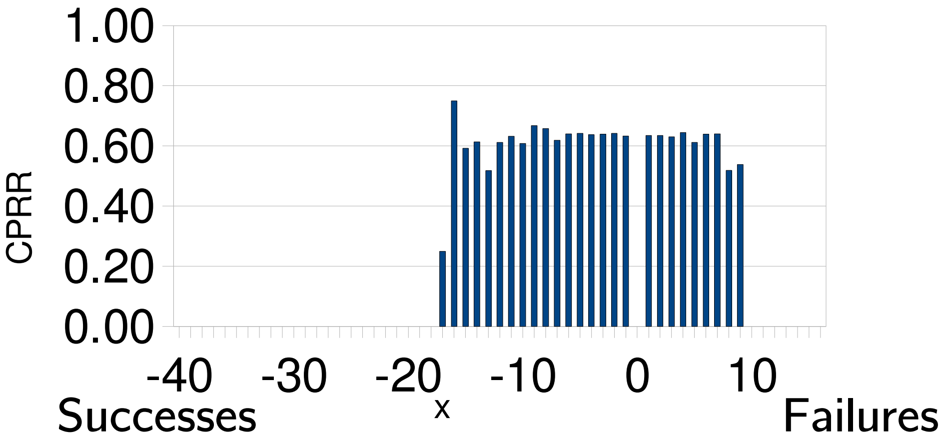
Real Signal

Power



Log Normal

Shadowing Model

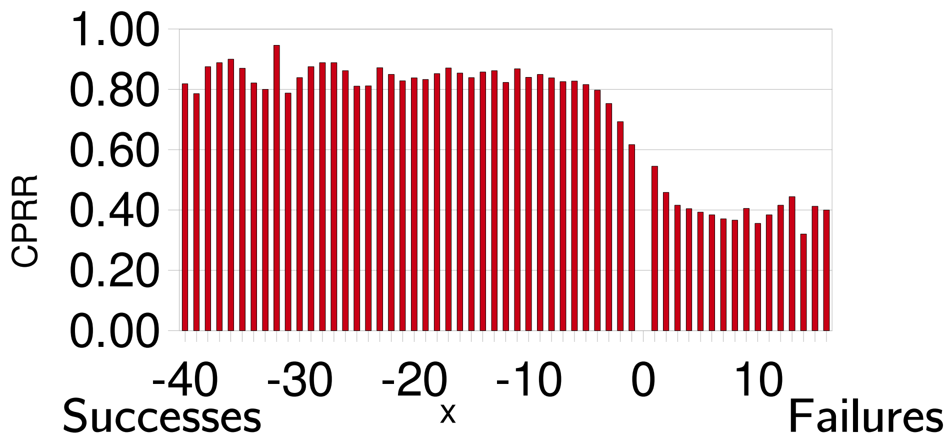


KW Distance = 0.20

CPDF: PRR = 58.5%

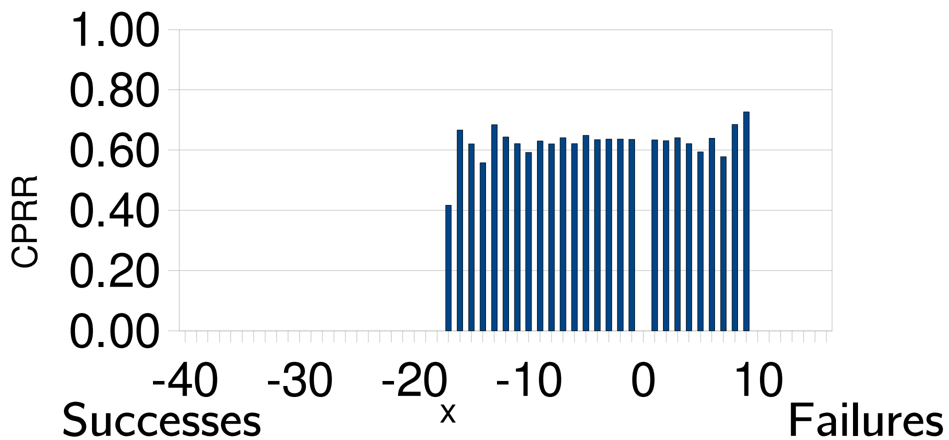
Real Signal

Power



TOSSIM

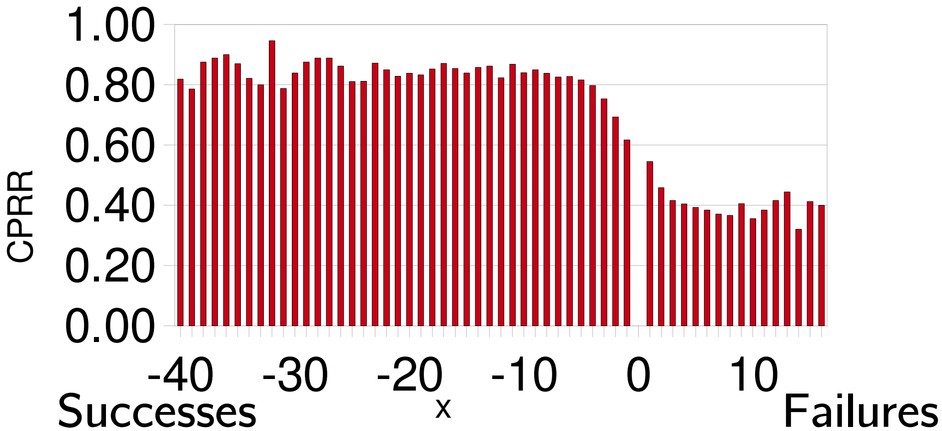
2.0.2



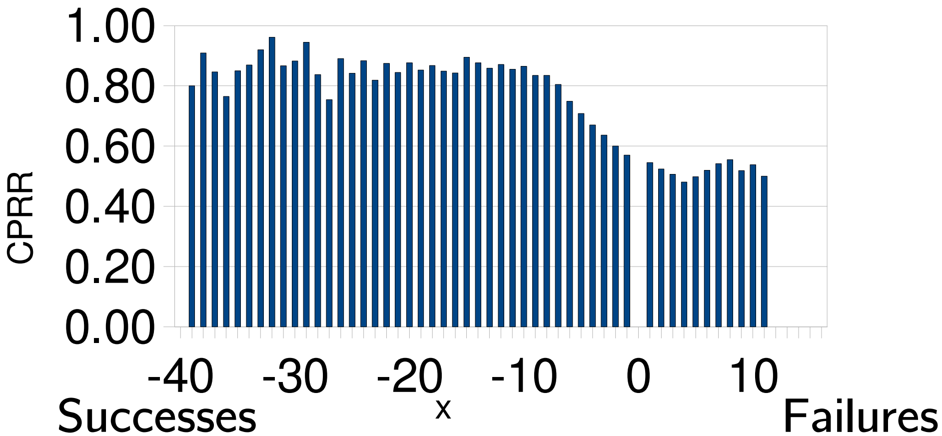
KW Distance = 0.21

CPDF: PRR = 58.5%

Real Signal Power



CPM+Expected Value PMF



KW Distance = 0.06

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Conclusions and Future Work

- KW distance < 0.1 for our experiments (substantially reduced as compared to current methods)
- PRR estimated to within 22% (typically to 10%)
- As expected, different assumptions work more effectively for different experiments.
- **Future work:** Development of an automated optimization layer to predict the most reasonable assumptions for a given environment.
- **Future work:** Investigate a signal power model that considers burstiness at many time scales, not just that of an individual packet.

Thank you.

Questions?

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CPM Model for Trace Histories

- Scan noise trace, keeping a history of size *k*.
- For each signature of *k* prior noise readings, construct the probability distribution for the next reading.

0	2	1	2	0	2	2	0	0	1	1	1	1	2	0	0	0	2	9	0

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

$k = 2$

HyungJune Lee, Alberto Cerpa, and Philip Levis, "Improving Wireless Simulation Through Noise Modeling." In Proceedings of the IPSN, 2007.

CPM Model for Trace Histories

- Scan noise trace, keeping a history of size *k*.
- For each signature of *k* prior noise readings, construct the probability distribution for the next reading.

0	2	1	2	0	2	2	0	0	1	1	1	1	2	0	0	0	2	9	0

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

$k = 2$

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CPM Sampling Demo

0	2				

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

30

$k = 2$

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CPM Sampling Demo

0	2	2			

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

$k = 2$

31

HyungJune Lee, Alberto Cerpa, and Philip Levis, "Improving Wireless Simulation Through Noise Modeling." In Proceedings of the IPSN, 2007.

CPM Sampling Demo

0	2	2	0		

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

$k = 2$

32

HyungJune Lee, Alberto Cerpa, and Philip Levis, "Improving Wireless Simulation Through Noise Modeling." In Proceedings of the IPSN, 2007.

CPM Sampling Demo

0	2	2	0	0	

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

$k = 2$

33

HyungJune Lee, Alberto Cerpa, and Philip Levis, "Improving Wireless Simulation Through Noise Modeling." In Proceedings of the IPSN, 2007.

CPM Sampling Demo

0	2	2	0	0	1

signature	0	1	2	9
00	33%	33%	33%	0%
01	0%	100%	0%	0%
02	0%	33%	33%	33%
11	0%	66%	33%	0%
12	100%	0%	0%	0%
20	66%	0%	33%	0%
21	0%	0%	100%	0%
22	100%	0%	0%	0%

34

$k = 2$

HyungJune Lee, Alberto Cerpa, and Philip Levis, "Improving Wireless Simulation Through Noise Modeling." In Proceedings of the IPSN, 2007.

CPM Sampling Result

- Modeled trace is not the same as the experimental trace:

0	2	2	0	0	1

0	2	1	2	0	2	2	0	0	1	1	1	1	2	0	0	0	2	9	0

- This increases the randomness of simulation output and thus decreases the predictability of the simulation.
- This allows for substantial representative simulation.

HyungJune Lee, Alberto Cerpa, and Philip Levis, "Improving Wireless Simulation Through Noise Modeling." In Proceedings of the IPSN, 2007.