# Wireless Link Simulations using Multi-level Markov Models Ankur U. Kamthe, Miguel Á. Carreira-Perpiñán and Alberto E. Cerpa

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### Introduction

Modeling the behavior of 802.15.4 links is a non-trivial problem because of the widespread heterogeneity in the quality of any given link over time. Moreover, links experience different level of dynamics at short and long time scales, which makes the design of a suitable model that combines the different dynamics at different timescales a difficult task.

### Contribution

We introduce novel multilevel approach involving Hidden Markov Models (HMMs)[1] and Mixtures of Multivariate Bernoullis (MMBs)[2] for modeling the long and short time scale behavior of links in wireless sensor networks.

## Modeling Approach



(a) Variation in Packet Reception of a link over time

#### The fundamental motivation for our modeling *approach is that observed traces display structure* at different temporal scales.

- Long-term dynamics: From Figure (a), we observe that over a period of minutes the link seems to switch between two states: one with  $PRR \approx 0.3$  and the other with  $PRR \approx 0.86$ .
- Short-term dynamics are variations in consecutive packet reception successes or failures. In a period of seconds, however, while the PRR may stay roughly constant at 0.3, it is more likely to observe a bursty sequence 00000001111 than a wildly oscillating sequence 010010100100.
- For realistic simulation, the model must replicate the multiscale structure.



- Level-2 or short-term models:
- model parameters.

## Summary and Future Work

- details, refer to [3].

1. A hidden Markov model (L2–HMM). This has (1) a set of  $Q_2$  short-term states and its associated transition probability matrix, and (2) a (univariate) Bernoulli emission distribution with parameter *p*.

2. A mixture of multivariate Bernoulli distributions (L2–MMB). This mixture has M components, and each component has W + 1 parameters: a mixture proportion and a vector  $\mathbf{p} = (p_1, \ldots, p_W)^T$  of Bernoulli parameters.

• Learning: Estimating the parameters of the M&M model is done by maximizing the loglikelihood of the given data set over all the

### Model Evaluation

- (CPDF).



- compared to the original traces (see Figure (c)).
- 2.5% whereas the average standard deviation of the simulated link PRR was 0.004.



(e) Distribution of Run lengths and CPDFs for original trace (f) Distribution of Run lengths and CPDFs for M&M trace

as seen in the training trace.

• Our model allows us to learn from data, not just bursts but far more complex behaviors. For

• The M&M model is a generalization of the Gilbert model [4].

• Transforming existing model parameters to simulate new environments using order of magnitud training samples by applying model adaptation techniques [5] is part of our future research agend

• The model can be extended to emit signal strength values, thus, modeling physical layer characte such as RSSI values of wireless traces.



• For each link, learn model parameters given data traces of length 230,400 ( $Q_1 = 6, Q_2 = 2$  and M = 20).

• For each model, sample a long sequence and compared performance on the basis of: (1) Packet Reception Rates (PRR), (2) Distributions of run lengths of 1's and 0's, and (3) Conditional Packet Delivery Function

• The simulated traces (see Figure (d)) are able to capture the long term dynamics quite accurately when

• Overall, the average difference between the PRR of the simulated and the original trace was less than



• Figure (e) and (f) plot the distributions of run lengths and CPDFs of 0's and 1's for the original and simulated traces, respectively. We can see that the M&M traces are able to simulate the longer runs/bursts

	References
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