DEEP LEARNING FOR ROBUST POWER CONTROL FOR WIRELESS NETWORKS

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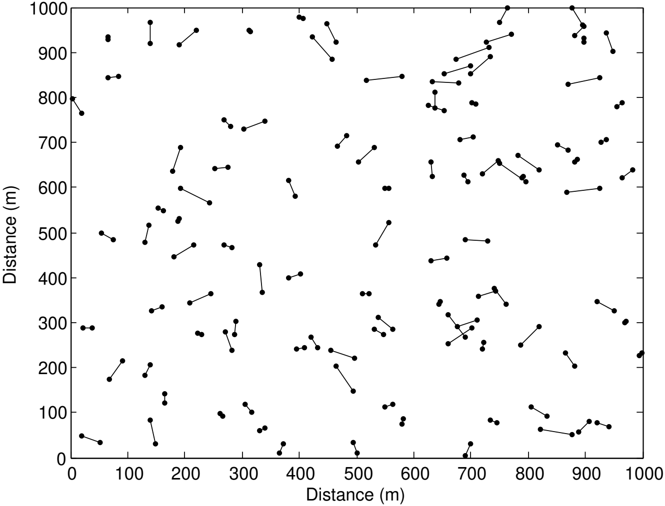
Robust Optimization of Wireless Networks

- Wireless channels have inherent uncertainty. Deterministic optimizations do not capture the realistic wireless environment.
- State-of-art robust optimization algorithms use statistical models to incorporate uncertainties into the solutions.
- However, this classic approach relies on ad-hoc mathematical models, which are hard to obtain and might not be truly accurate. Further, the parameters of these models are often difficult to estimate.
- This paper proposes to use machine learning (ML) to learn robust solutions from the uncertainty samples, effectively providing a more direct representation of the uncertainties.

Link Power Control in Device-to-Device Networks



Robust Sum Rate Maximization

- For given instantaneous channel realizations and a set of power control decisions $\{x_i\}$, the achievable rate of each link is:

$$R_i = W \log\left(1 + \frac{g_{ii} p_i x_i}{\Gamma(\sum_{j \neq i} g_{ij} p_j x_j + \sigma^2)}\right), \tag{1}$$

- Path-loss components can be accurately obtained.
- But, shadowing and fast-fading may be harder to measure. In this work, they are regarded as channel uncertainty.

Goal: *Design a centralized controller to perform robust power control based only on path-loss as inputs, but robust to shadowing/fast-fading.*

Notion of Robustness

- We adopt the concept of outage capacity for ensuring robustness on each individual link, then optimize robust sum rate over the network.

- Given a fixed outage probability γ, the robust rate $\hat{R}_i$ is:

$$\Pr[R_i < \hat{R}_i] \leq \gamma, \ \forall i \tag{2}$$

- The robust sum-rate optimization problem formulation:

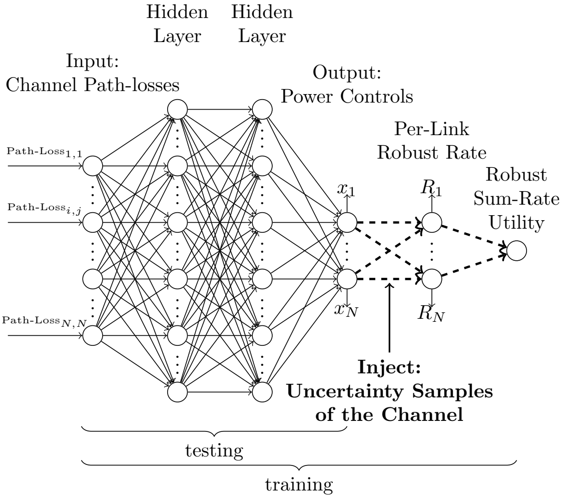
$$\underset{\mathbf{x}}{\text{maximize}} \quad \sum_{i=1}^{N} \hat{R}_i \tag{3a}$$

$$\text{subject to} \quad 0 \leq x_i \leq 1, \ \forall i. \tag{3b}$$

Learn Robust Solutions from Uncertainty Samples

- Accurate uncertainty models are typically difficult to obtain.
- Instead, we aim to learn robust power control strategy from uncertainty samples of the channels.
- While uncertainty is hard to measure for online applications, uncertainty samples can be easily collected for offline use.
- We design novel neural network model in which the uncertainty samples can be **injected** into the unsupervised training process.
- The deep neural network architecture is highly flexible. It directly learns the mapping from the path-loss input to the robust sum rate.

Novel Neural Network with Uncertainty Injection



Uncertainty samples are injected at the last training stage only.

Neural Network Architecture Details

- The neural network is fully-connected, with 3 hidden layers.
- Each hidden layer has $4N^2$ units (where N is the number of D2D links), each with ReLu non-linearity.
- The output layer for power control decisions has N units, each with Sigmoid non-linearity for its desired range, corresponding to x_i.

Robust Optimization via Unsupervised Learning

- Unsupervised learning is crucial for uncertainty injection training, avoiding the effort for obtaining *targets* for each channel.
- For each power control output $\{x_i\}$, we compute the robust sum-rate objective, then perform gradient-ascent to improve model parameters.
- Computation of each user's instantaneous rate requires full CSI.
- We inject many samples of the channel realization to obtain an empirical approximation of the γ-percentile rate.

Gradient-Ascent over Injected Samples

- Despite the complexity of the actual uncertainty distribution, injecting samples doesn't change the differentiability of the mapping.
- The prevalent gradient-based training is readily adaptable on our neural network structure.
- Denote the collective neural network parameters as W, and the set of CSI corresponding to the γ-percentile rate R_i^γ under $\{x_i\}$ as $\{g_i\}$.
- The gradient of the robust sum-rate with respect to the neural network parameters is just $\sum_{i=1}^{N} \frac{\partial R_i^\gamma}{\partial W}$, where different sets of $\{g_i\}$'s are involved in different links.

Wireless Network Model

- Full frequency reuse with 5MHz bandwidth at 2.4GHz carrier frequency; 1.5m antenna height and 2.5dB antenna gain.
- Additive white Gaussian noise at -169dBm/Hz
- SNR gap at 6dB
- Max transmit power is set to be constant across each link at 40dBm
- Short-range outdoor model ITU-1411 distance-dependent pathloss

Simulation Settings

- To validate the generalization ability of our method, we provide the simulation results for two settings with different parameters.

Table: Wireless Environment

Setting	Number of Links	Region Area (m^2)	Direct-Link Distance Distribution
A	20	1500×1500	10m∼40m
B	20	2000×2000	5m∼70m

- 1000 testing wireless networks are generated under each setting.

Robust Sum Rate

- We set $\gamma = 5\%$ as the tolerable outage probability for all links. The corresponding evaluation results are as follows:

Table: Robust Sum-Rate Performance

	A	B
Fractional Programming	104.2Mbps	149.6Mbps
Deep Learning **without** Uncertainties Injection	112.9Mbps	155.2Mbps
Deep Learning **with** Uncertainties Injection	**127.7Mbps**	**188.1Mbps**
Percentage Improvement	13%	21%

Cumulative Distribution of Robust Sum Rate

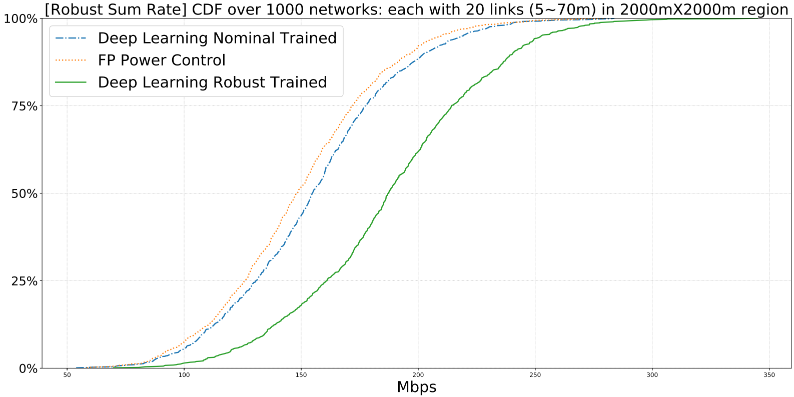


Figure: Cumulative distribution of robust sum-rates.

Rates Visualization

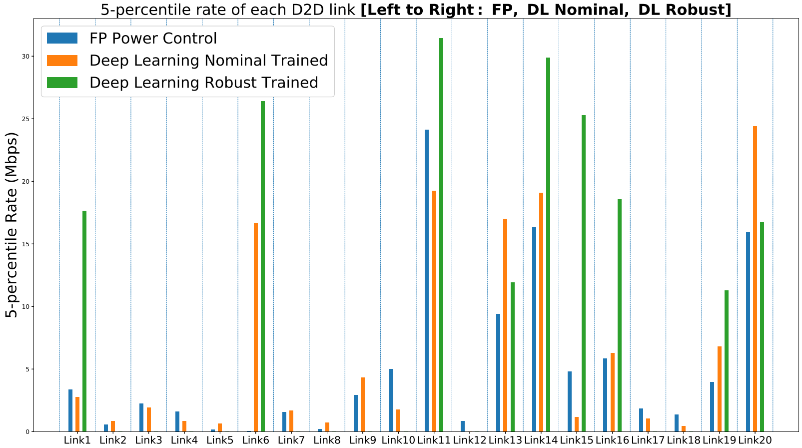


Figure: Robust rate for each link in a wireless network.

Robust Power Control Strategy

- By visualizing the 5%-outage rate, we can see that the neural network has learned to more heavily utilize the stronger links and to de-emphasize the weaker links.
- By giving up the weaker links, it reduces the number of non-zero interference terms in SINR expressions.
- These terms are subject to channel uncertainty fluctuations and can be detrimental to the sum-rate under unfavorable channel conditions.
- An additional benefit: our model achieves the performance with much less power (**39.55%** in Setting A and **48.79%** in Setting B of FPLinQ's average allocated power), thus also being power-efficient.

Conclusion

- We propose a novel neural network architecture for robust power control, trained via uncertainty samples injection.
- Based only on path-loss inputs, our model achieves satisfying sum-rate results against uncertain shadowing and fast-fading.
- Key features of the robust sum-rate maximization framework:
  - Incorporating uncertainty only through its samples, thus being compatible with arbitrary uncertainty distributions.
  - Highly flexible to different optimization objective formulations.
  - Using unsupervised learning to avoid costly target preparation.
  - Learning novel yet interpretable power allocation strategy.