Deep Learning for Frame Error Probability Prediction in BICM-OFDM Systems

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Motivation

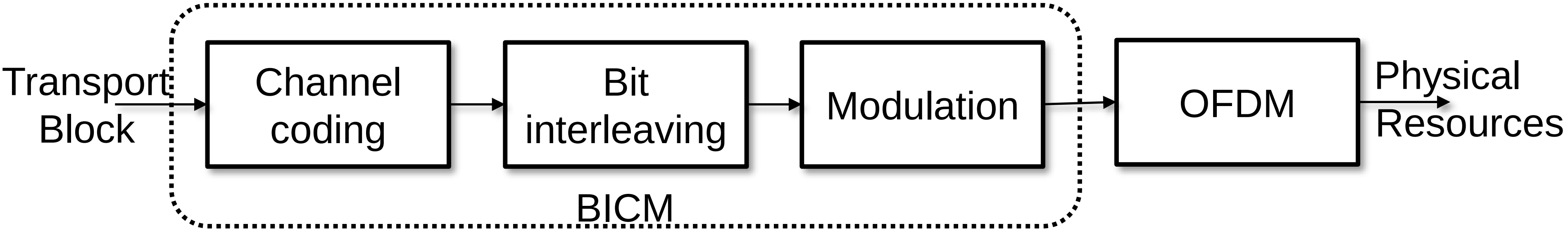
Practical radio systems need to set link parameters in stochastic radio channels.

Radio Baseband

Radio channels vary with time and over frequency.

Bit-Interleaved coded modulation (BICM) adds controlled redundancy to source data.

Orthogonal frequency division multiplexing (OFDM) splits the radio channel into several orthogonal "subcarriers".

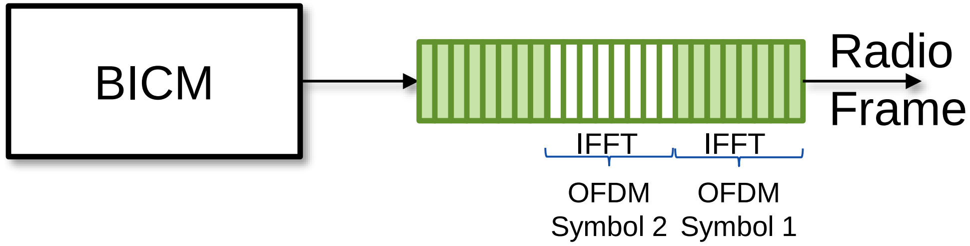


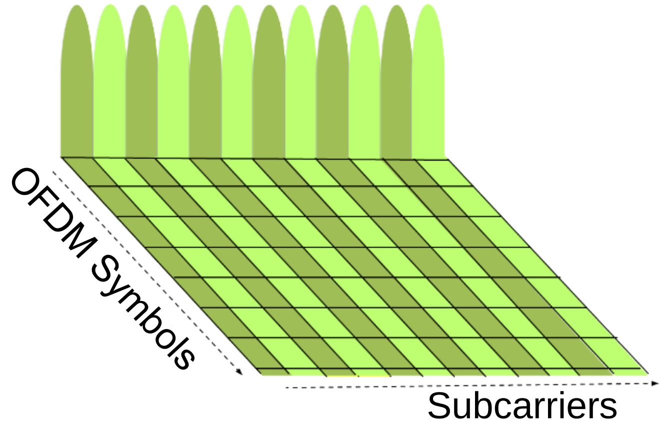
Transmission Unit: Radio Frames

Each transmission unit, “frame”, spans several OFDM symbols and subcarriers.

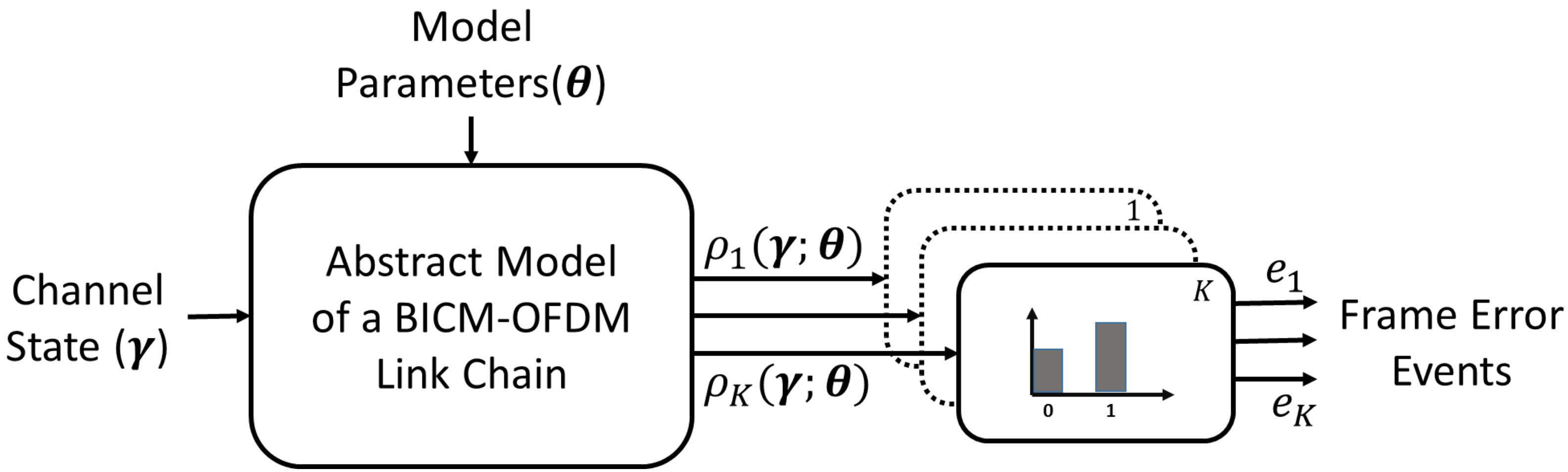
Channel state characterized by per-subcarrier signal to interference and noise ratio vector, $\boldsymbol{\gamma}$.

$\boldsymbol{\gamma}$ is assumed constant over a frame.





Radio Link Model



Frame Error Probability (FEP)

The frame error probability (FEP) distribution is:

$$P_{E_k|\Gamma}(e_k|\boldsymbol{\gamma};\boldsymbol{\theta}) = \rho_k^{e_k}(1-\rho_k)^{1-e_k}$$

$$\rho_k = f_k(\boldsymbol{\gamma},\boldsymbol{\theta}_k)$$

$\boldsymbol{\gamma}$ is distributed according to the channel fading profile.
e_k: $E_k \sim \mathrm{Bern}(f_k(\boldsymbol{\gamma},\boldsymbol{\theta}))$ for some unknown f_k.
$\boldsymbol{\theta}$ is the deterministic model parameter vector.

We need to estimate ρ_k to select the optimal transmission configuration e.g., that maximizes the throughput.

Traditional approach

Compress the state vector to an ”effective” scalar value

$$\rho_k = f_k(\boldsymbol{\gamma}, \boldsymbol{\theta}) \approx g_k(\gamma_{k,\text{eff}}, \beta)$$

Simplified problem: estimate a suitably parameterized g_k.

However, compression leads to loss of information.

Effective Exponential SINR

A common effective SINR formulation is

$$\gamma_{\text{eff}}^{\text{AWGN}} = -\beta_k \sum_{p=1}^{P} e^{-\frac{\gamma_p}{\beta_k}}, \qquad \boldsymbol{\gamma} = [\gamma_1, \dots, \gamma_P],$$

known as the Exponential Effective SINR metric (EESM).

Then $\rho_k \approx g_k^{\text{AWGN}}(\gamma_{k,\text{eff}})$ is read from simulation-based LUTs.

The parameters β_k can determined through data-fitting over some training data.

Machine learning approach

Directly learn the high-dimensional mapping $\rho_k = f_k(\boldsymbol{\gamma}, \boldsymbol{\theta}_k)$

A learning-based approach has been studied using k-Nearest neighbors (kNN) for the same problem[1].

kNN does not provide any insights into the optimality of the learned mapping.

Neural networks are an attractive tool for parameterizing high-dimensional models.

1. R. C. Daniels, C. M. Caramanis, and R. W. Heath (2010), “Adaptation in Convolutionally Coded MIMO-OFDM Wireless Systems Through Supervised Learning and SNR Ordering,”

Our approach: Neural networks

Maximum likelihood estimation of neural network parameters approximates the posterior conditional FEPs[1,2].

For a large number of i.i.d. samples,

$$C(\widehat{\boldsymbol{\theta}}) \xrightarrow{N\to\infty} E\{\ln P(E_k|\boldsymbol{\Gamma};\widehat{\boldsymbol{\theta}})\}$$
$$= E\left\{\ln \frac{P(E_k|\boldsymbol{\Gamma};\widehat{\boldsymbol{\theta}})}{P(E_k|\boldsymbol{\Gamma};\boldsymbol{\theta})}\right\} + E\{\ln P(E_k|\boldsymbol{\Gamma};\boldsymbol{\theta})\}$$

Minimizes the cross entropy loss between network outputs and frame error events

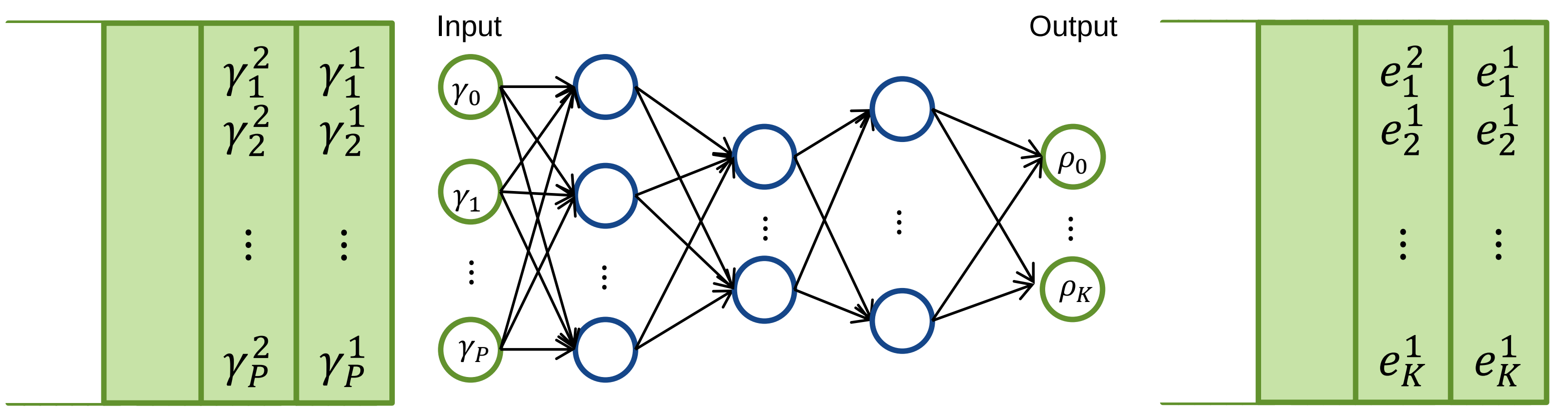
K parallel binary classification problems.

1. H. Gish (1990), “A probabilistic approach to the understanding and training of neural network classifiers”.
2. M. D. Richard and R. P. Lippmann (1991), “Neural Network Classifiers Estimate Bayesian a Posteriori Probabilities”.

Training phases

Inputs: $\boldsymbol{\gamma}^{\boldsymbol{n}}$ for $n = 1, \dots, N$ frame realizations.

Targets: $\mathbf{e}^n$ containing error events for each transmission configuration.



Results: Simulation setup

LTE-like radio link chain with ideal channel estimation.

Select the link configuration to maximize expected throughput in each frame,

$$k^{\text{opt}} = \underset{k}{\text{argmax}}\, T_k(1 - \hat{\rho}_k)$$

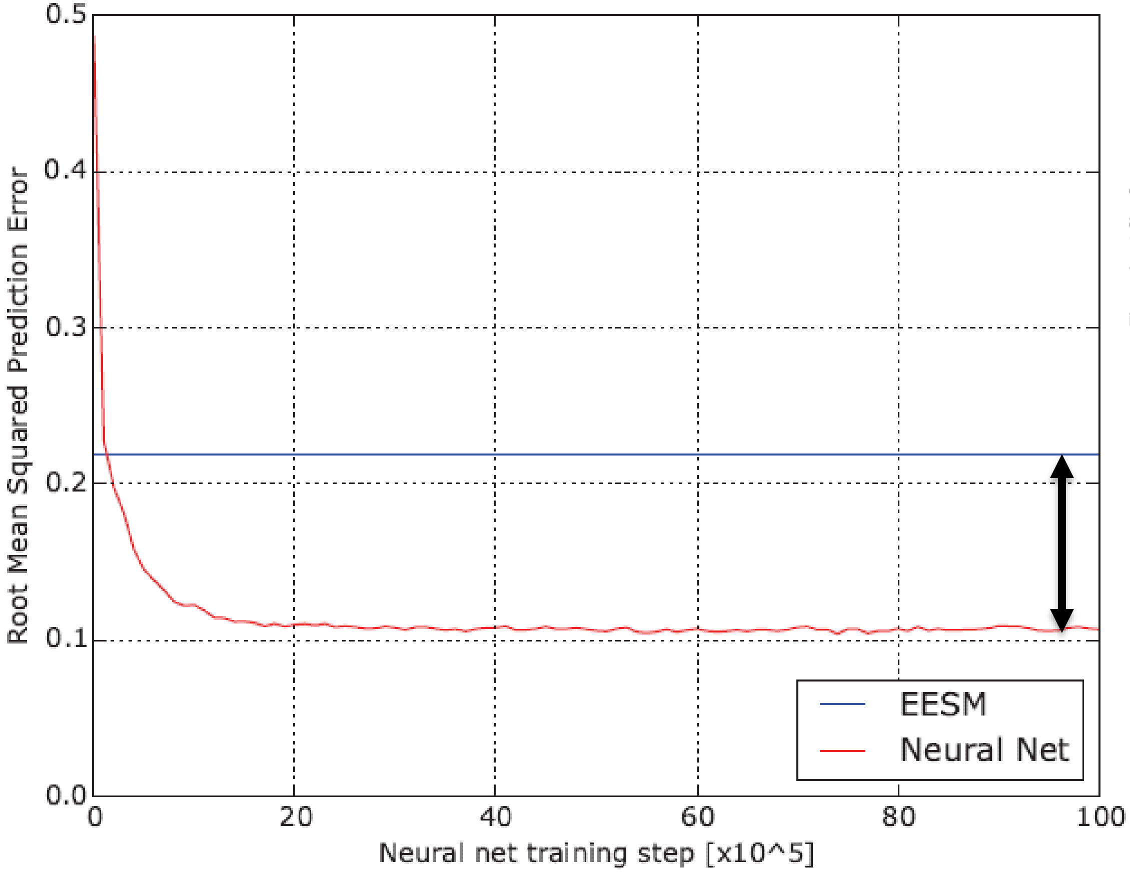
TABLE II
SIMULATION PARAMETERS

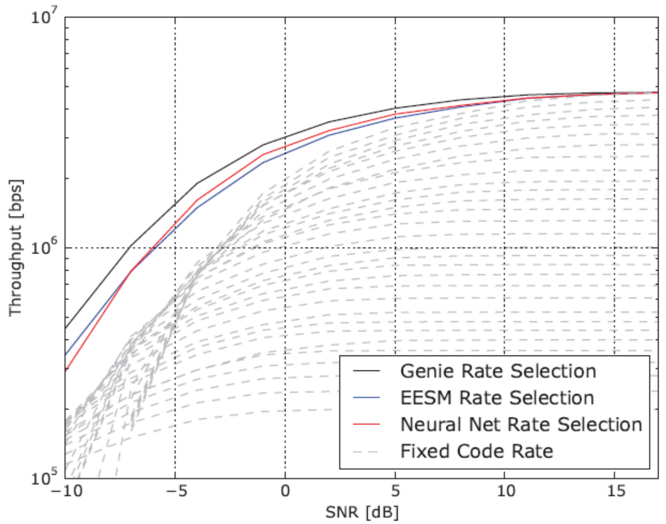
Simulation Parameter	Value
Channel Model	EPA
Carrier Frequency	2×10^9 Hz
FFT Size	1024
Subcarrier Spacing	15×10^3 Hz
Frame Duration	10^{-3} s
Number of Frame OFDM Symbols	12
Number of Used Subcarriers	600
Modulation	QPSK
Channel Coding	Turbo
Nominal Code Rate	$1/3$
Effective Code Rates	[0.01, 0.02..., 0.32]

NEURAL NETWORK LAYOUT

Layer	Output Dimensions
Input	P
Dense + ReLU	P
Encoder + ReLU	10
Dense + ReLU	K
Dropout	K, drop probability = 0.2
Output + Sigmoid	K

Results: Performance





Improvement in the FEP prediction

Conclusions

Neural networks can model posterior probabilities in highly complex models.

Proof of concept that link throughput can be improved over traditional compression-based approaches.

Further, nonlinear effects e.g. related to transmit/receive impairments may also be learnt from data.

Thank you!