

# Neural Network-Based Equalizer Hardware-Accelerator

PRESENTED TO  
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# Why NN Equalizer

Digital communication systems suffer from channel impairments such as:

- ▶ Inter-symbol interference (ISI)
- ▶ Nonlinear distortions
- ▶ Noise and fading

Traditional equalizers (LMS / MMSE) struggle with:

- Nonlinear channel distortion
- Time-varying multipath fading
- High-speed real-time processing

# Why NN Equalizer

Recent NN-based equalizers have been shown to **outperform conventional methods** (higher Q-factor/BER) while using comparable numbers of real multipliers.

For example, a biLSTM+CNN equalizer matched DBP performance with +1.7 dB Q-factor gain over a CDC baseline in experiments

# Why IC Hardware Instead of DSP?

## DSP Equalizer

Programmable but slower

Higher power consumption

General-purpose design

Better for software flexibility

## Neural Equalizer IC

Ultra low-latency inference

Very low dynamic power

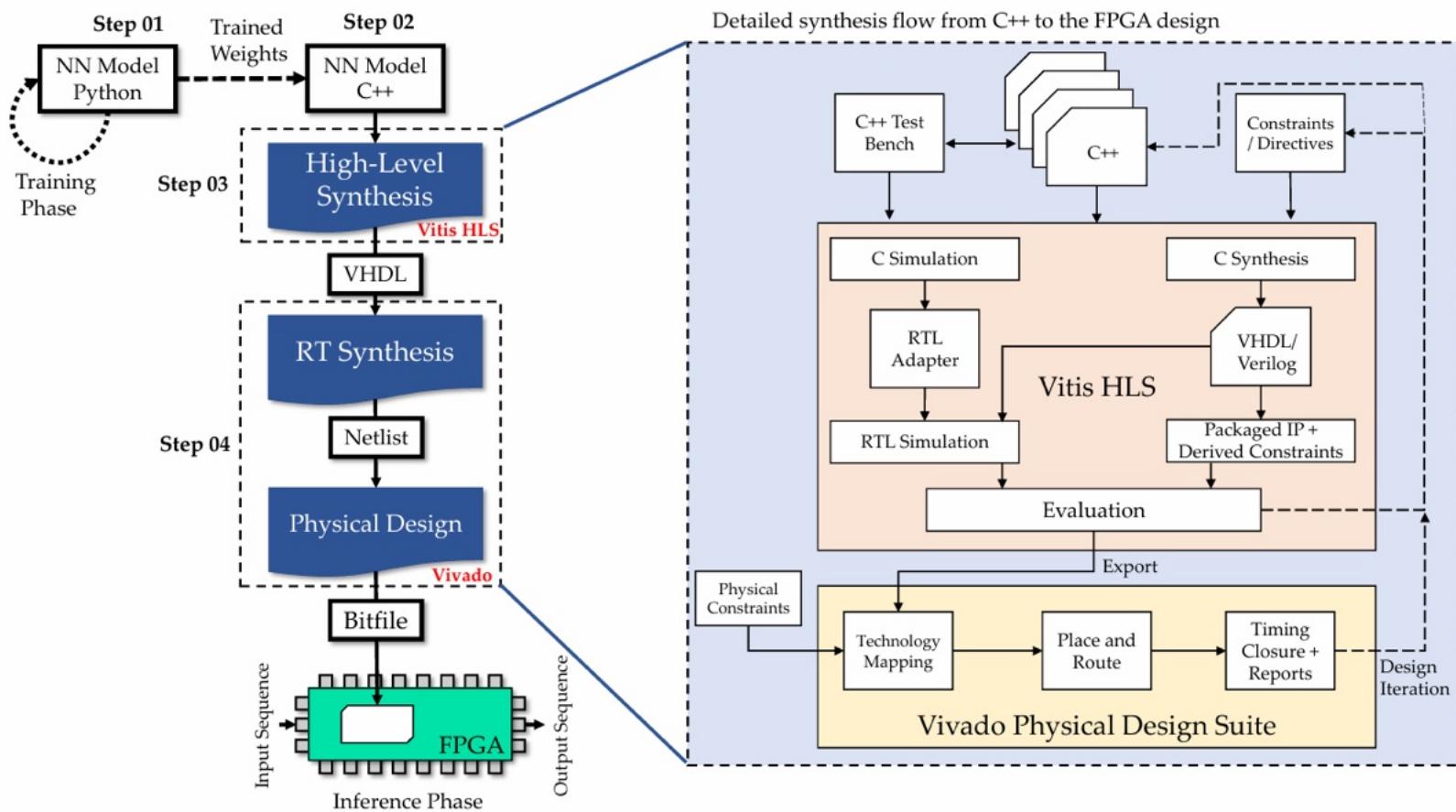
Optimized for equalization only

Better for IoT & high-speed hardware

# Objectives

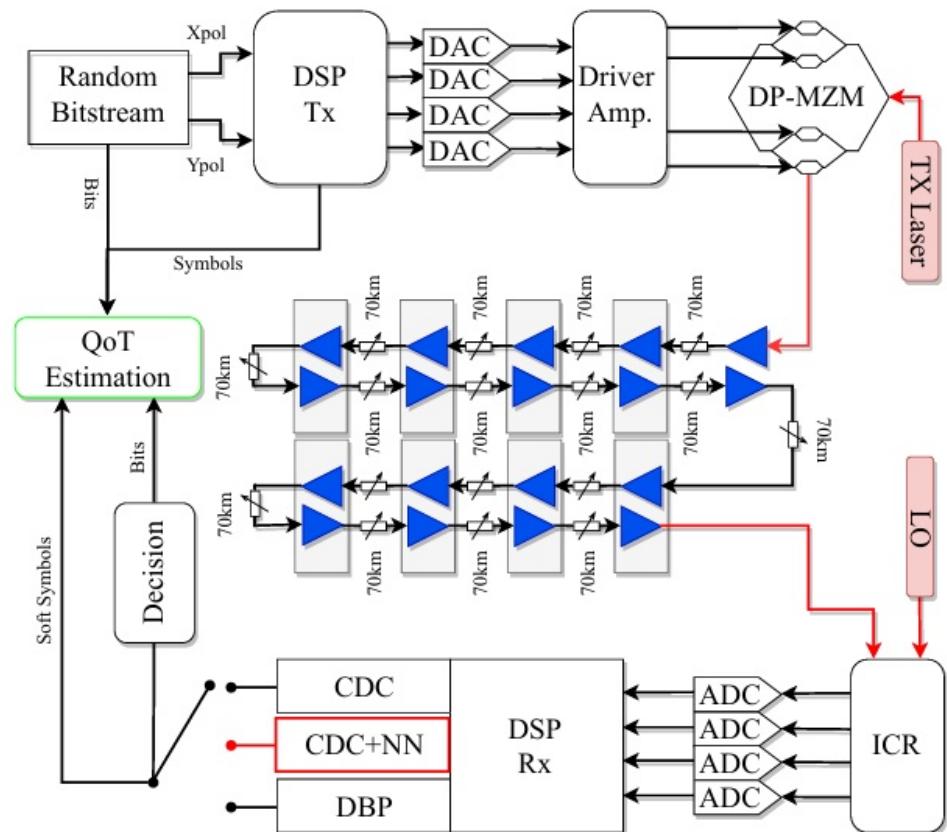
- ▶ **Implement** offline FPGA realization of NN equalizer for nonlinear impairment compensation.
- ▶ **Pipeline development:** Convert trained Python models to fixed-point C++ and then to FPGA IP via high-level synthesis (HLS).
- ▶ **Benchmarking:** Compare NN equalizer performance (pre-FEC BER/Q-factor) against 1-Step DBP and standard chromatic dispersion compensation CDC (using simulated and experimental data).
- ▶ **Hardware analysis:** Evaluate activation-function approximation methods, FPGA resource utilization, and achievable latency/throughput for target bit-rates.

# Workflow



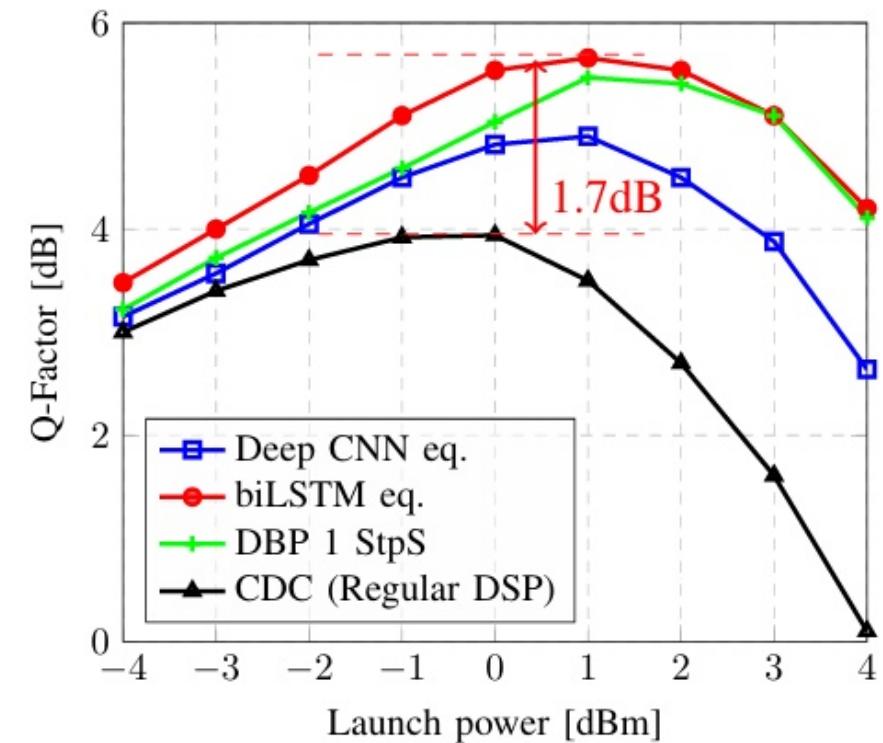
# Experimental Setup

- ▶ **Transmission link:** Single-channel dual-polarization 16QAM at 34 GBd over  $17 \times 70$  km spans of large-effective-area fiber (LEAF).
- ▶ **Receiver DSP:** Coherent optical RX (integrated coherent front-end).
- ▶ **NN Equalizer:** Processes the soft output of the DSP (before symbol decisions) to mitigate residual fiber nonlinearity.
- ▶ **three possible equalization paths (for comparison):**
  1. **CDC** (Chromatic Dispersion Compensation)
  2. **CDC + NN** (standard dispersion compensation + neural-network nonlinear equalizer)
  3. **DBP** (Digital Backpropagation)



# Experimental Setup

- ▶ biLSTM outperforms DBP, especially in noise-dominated regions.
- ▶ Deep CNN Equalizer Performs Well but Worse Than biLSTM & DBP.
- ▶ In real experiments, NNs also learn and compensate:
  1. Hardware distortions (ADC/DAC, drivers)
  2. Polarization mismatch
  3. Connector loss
  4. Fiber parameter variations

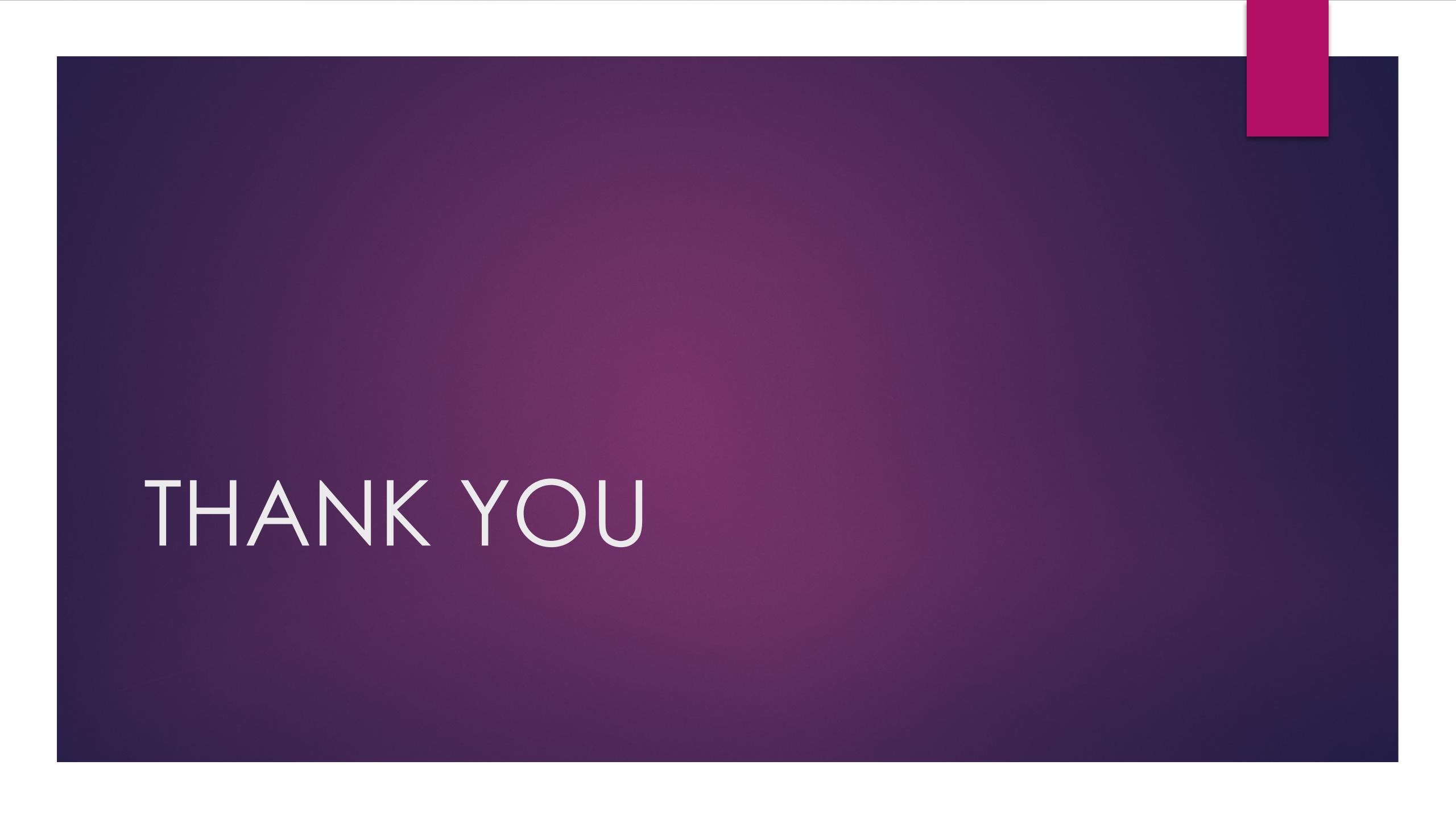


# Neural Network Design

- ▶ **Architectures:**
  - a) biLSTM+CNN equalizer: one bi-directional LSTM layer (35 hidden units) followed by a convolutional layer (total 70 filters).
  - b) Deep CNN equalizer: two convolutional layers (each 35 filters,  $1 \times 11$  kernel, zero-padding) followed by an output conv layer.
- ▶ **Network details:** Hidden layers use hyperbolic-tangent (tanh) activation; the final output layer uses a linear (identity) activation.
- ▶ **Training:** Both models trained with MSE loss and Adam optimizer. Hyperparameters: mini-batch size 200, learning rate  $5 \times 10^{-4}$ . Training set of  $2^{20}$  symbols was used, with early stopping on validation BER. Models were trained for 30,000 epochs on a fixed dataset (sampling  $2^{18}$  new inputs each epoch).
- ▶ **Results (software):** After training, both NNs significantly reduced BER. The biLSTM+CNN model consistently outperformed the pure CNN equalizer in simulations.

# Possible Adjustments

- ▶ Use a different channel type (e.g. wireless channel).
- ▶ Optimize the design to suit specific applications, like IOT.
- ▶ Synthesize for ASIC target library



THANK YOU