Unlocking Vehicular Communication with Fluid Antennas and Deep Learning

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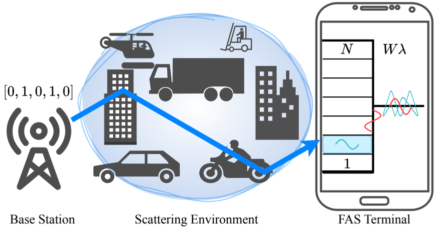
Agenda

1. FAS
2. IEEE 802.11p
3. The HPA problem
4. Where to apply DL?
5. Our Proposal
6. Results

Outline

What is FAS?

- Fluid antennas enable a **single physical antenna** to behave like many *virtual antennas* distributed along an aperture of length $W\lambda$.
- Key idea: instead of building many antennas and RF chains, as in MIMO, we 'move' the effective radiation point across different positions, called **ports**.
- One (or a subset of) port(s) can be activated at a time to harvest **spatial diversity** at a very low cost.



Design parameters

Aperture size, number of ports, N, port spacing, switching latency, and spatial correlation (often Jakes-like).

Why it matters for V2X?

- Vehicular channels change very rapidly, and deep fades occur at sub-wavelength distances due to high mobility and multipath.
- FAS performs spatial sampling of the channel response. It can dynamically select the port with the highest instantaneous SNR.
- Only one port (or a limited subset) is activated at a time, minimizing hardware complexity and cost.
- In contrast to conventional MIMO systems, FAS achieves spatial diversity through **motion**.

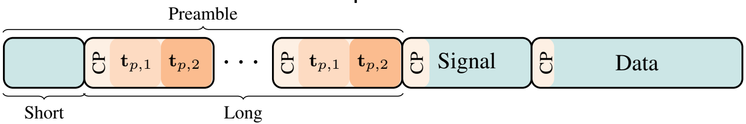
General Idea

Instead of adding antennas, we *move the effective radiation point of a single antenna*.

Outline

IEEE 802.11p Air Interface

- IEEE 802.11p is a standard enabling vehicular communication.
- **Frequency/BW:** 5.9 GHz, 10 MHz (narrower than 802.11a/g).
- **OFDM:** $K = 64$ subcarriers, $K_{\text{on}} = 52$ active (data: 48 + pilots: 4).
- **Preamble:** One short, and two long training symbols for synchronization, coarse carrier frequency offset, and channel estimation.
- **Signal** and **data** sections follow the preamble.



Why this matters?

The preamble enables initial **LS estimation across all FAS ports**, and the data section is used to improve channel estimates using the **data-pilot aided (DPA)** method.

Outline

Nonlinear HPA distortions

- **High PAPR in OFDM** drives the amplifier into its nonlinear region.
- This causes **AM/AM** (amplitude) and **AM/PM** (phase) distortion.
- To reduce the effects of nonlinearities, the HPA operates at a given input back-off (**IBO**) from the 1 dB compression point, which trades efficiency for linearity.
- We model the distorted HPA's output, $\mathbf{u}[n]$, with the **Bussgang decomposition**

$$\mathbf{u}[n] = \mathbf{x}[n] + \tilde{\delta}[n]/\gamma_0$$

where $\mathbf{x}[n]$ is the input, γ_0 is a complex gain, and $\tilde{\delta}[n]$ is an uncorrelated **non-linear** distortion term.

Takeaway

Channel estimation must remain robust to nonlinear distortion even though it impacts both pilot and data subcarriers.

Outline

What is Deep Learning?

- Subarea of ML that uses neural networks with multiple layers.
- **Deep Learning (DL)** can learn complex nonlinear mappings from data.
- Unlike traditional algorithms, DL **learns directly from raw features**. No manual design of features like channel statistics or models is required.
- Typical DL architectures:
  - **DNNs:** Standard fully connected networks for general pattern recognition.
  - **CNNs:** Learn spatial or frequency-domain features.
  - **RNNs/LSTMs:** Has memory and learns temporal correlations.

Goal

Find a model that generalizes across different channel conditions and distortion patterns.

Why Deep Learning Helps in Wireless Links?

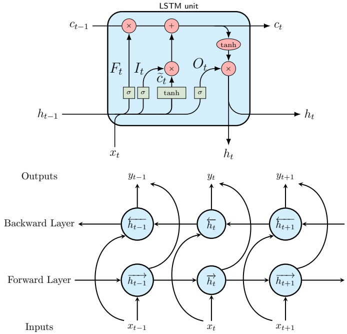
- Traditional channel estimators (e.g., LS, MMSE) assume **linear models** and **stationary noise**.
- In practice, FAS/V2X channels are **nonlinear, time-varying, and spatially correlated**.
- DL models can learn:
  - Nonlinear distortion patterns (from HPA or hardware mismatch).
  - Temporal evolution of the channel and spatial correlations across the ports.
  - A mapping from distorted pilots and data into cleaner channel estimates.

Benefits

DL-based estimators achieve lower error and better detection performance in mobility and nonlinear regimes than linear estimators.

Where to Apply Deep Learning in FAS/V2X

Deep learning can be inserted at different points in a communication system.



- **At the receiver:**
  - Predict the best FAS port without evaluating all ports.
  - Refine **LS/DPA channel estimates**.
- **At the transmitter:**
  - Learn power-control or beamforming decisions from historical CSI.
- **Cross-layer use:**
  - Predict link reliability and schedule port-switching to reduce latency.

In this work, we focus on receiver-side DL for best-port prediction and channel estimation refinement.

Outline

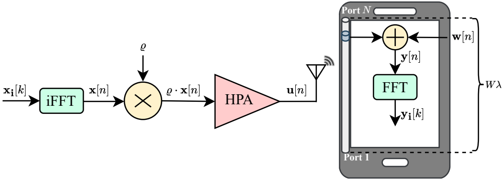
System Model: Overview

Transmitter (Tx)

- Single-antenna
- **Signal:** IEEE 802.11p OFDM
- **Impairment:** HPA nonlinear distortion

Receiver (Rx)

- **Antenna:** FAS with $N = 100$
- **Channel:** Freq-selective Rayleigh
- **Correlation:** Jakes-like



Received Signal (per subcarrier k, symbol i)

$$\mathbf{y}_i[k] = \mathbf{h}_i[k]\,\mathbf{u}_i[k] + \mathbf{w}_i[k]$$

System Model: Estimation Flow

The channel estimation process with FAS consists of three steps:

1. **LS Estimation (per port):** Use the training symbols from the preamble to get an initial LS estimate for *each* port.

$$\hat{\mathbf{h}}_{\mathrm{LS}}[k] = \frac{\mathbf{y}_{p,1}[k] + \mathbf{y}_{p,2}[k]}{2\,\mathbf{p}[k]}$$

2. **Port Selection:** Select the *port* with the highest SNR for data reception.

$$l_{\textsf{selected}} = \arg\max_{l \in \mathcal{N}} \mathrm{SNR}_l$$

3. **DPA Update (Symbol-by-Symbol):** For the selected port, use the decoded data symbol, $\mathbf{d}_i[k]$, to update the channel estimate for the next symbol, $i+1$.

$$\hat{\mathbf{h}}_{\mathrm{DPA}_i}[k] = \frac{\mathbf{y}_i[k]}{\mathbf{d}_i[k]}$$

Problem

DPA estimates degrade quickly under high mobility (due to error propagation across the OFDM symbols) and HPA distortion.

Proposal 1: DL for Port Prediction

Problem: Evaluating the SNR at all $N = 100$ ports creates a significant overhead and adds latency to the communication.
Solution: Use DL models to predict the *best port* from all N by observing only a small subset, N_{observed}.

Port Prediction Workflow

- **Input:** SNR values from N_{observed} ports ($N_{\text{observed}} < 100$).
- **Output:** The predicted index of the best port (from 1 to 100).

- The model learns spatial correlations across ports and uses them to predict the SNR at all ports.
- **Goal:** Optimize the BER performance by receiving the signal through the port with the highest SNR.

Proposal 2: DL as a Channel Estimate Refiner

Problem: DPA-based estimates degrade quickly due to mobility and HPA distortion.
Solution: Use the coarse DPA estimates as *inputs* to a DL model, which refines the estimates.

DL-Aided Estimation (Symbol-by-Symbol)

`Coarse DPA` → `[ DL-Refiner ]` → `Improved Channel Estimate`

- The DL model learns the nonlinear patterns from the HPA and the time-varying channel statistics that analytical models don't.
- We assess both **DNN** and the recurrent **LSTM** models for this task.

Outline

Sytem Setup

Simulation Setup

- **IEEE 802.11p:** $K = 64$, $K_{\text{on}} = 52$, 10 MHz
- **FAS:** $N = 100$ ports, Jakes correlation
- **Channel:** ITU Vehicular-A
- **Speeds:** $50\,\text{km/h}$, $100\,\text{km/h}$ and $200\,\text{km/h}$
- **Mod/HPA:** $16-$QAM, IBO$=4\,$dB

Models and Metrics

- **Estimators:** DPA, DPA-DNN, DPA-LSTM (Symbol-by-Symbol)
- **Metrics:** NMSE, BER

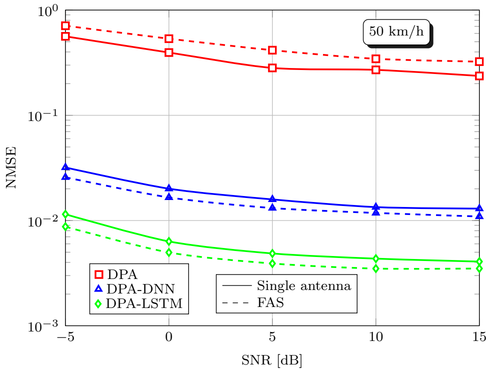
DL Model Architectures

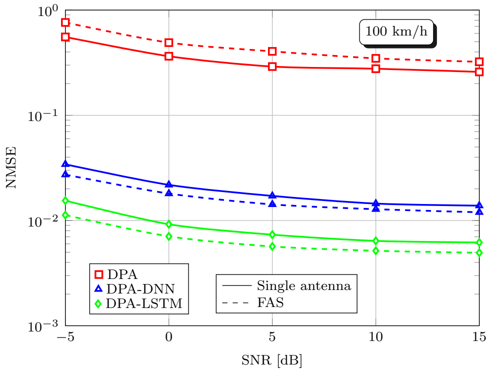
Model	Configuration
DPA-DNN	3 Layers (40-20-40)
DPA-LSTM	1 Layer (52 Units)

DL Training Parameters

Parameter	Value
Training samples	8000
Testing samples	2000
Batch size	32
Epochs	500
Optimizer	Adam

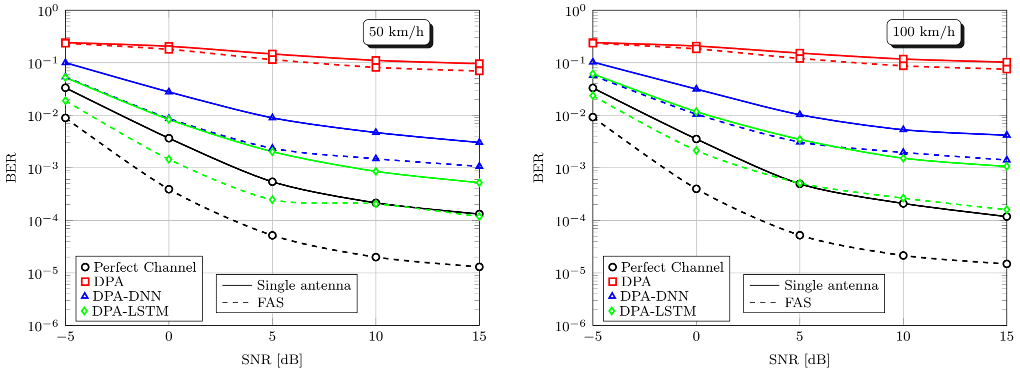
FAS vs Single Antenna (NMSE)





- DL-based estimators achieve superior NMSE performance when FAS is used.
- DPA-LSTM shows the lowest NMSE.

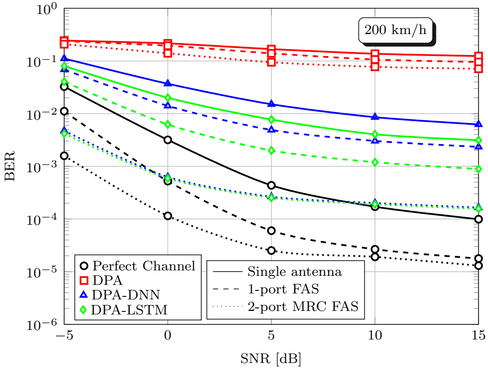
FAS vs Single Antenna (BER)



- FAS reduces BER for all estimation methods compared to a fixed single antenna.

High Speed (200 km/h) and MRC

- At 200 km/h, performance degrades due to high Doppler shifts and DPA error propagation.
- We explore 2-port Maximum Ratio Combining (MRC) to improve resilience.

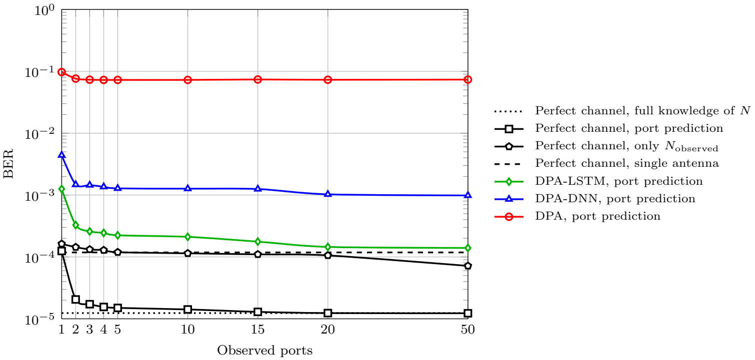


Port Prediction from Few Observations

- Reduce overhead by observing only N_{observed} linearly-spaced ports instead of all $N = 100$.
- Our LSTM-based predictor achieves near full-knowledge BER by observing only **15 ports**.

Port Prediction Model

Parameter	Value
Input Dim.	N_{observed}
Layers	LSTM (64, 32), FC (64)
Output Dim.	N (Binary labels)
Loss Func.	Binary Cross-Entropy
Optimizer	Adam



Complexity

Per-Symbol Complexity

- DPA: $\mathcal{O}(K_{\text{on}})$
- DPA-DNN: $\mathcal{O}(K_{\text{on}} \cdot N_{\text{observed}})$
- DPA-LSTM: $\mathcal{O}(K_{\text{on}}^2 \cdot N_{\text{observed}})$

Design Levers

- Reduce N_{observed} via port prediction
- Use lightweight models (e.g., Liquid NN)
- Trade NMSE/BER vs. latency

Conclusions and Future Work

Conclusions

- FAS + DL estimators are a robust solution for IEEE 802.11p under mobility and with HPA nonlinearities.
- The proposed workflow (Preamble Selection + DL Refiner + Port Prediction) successfully reduces both estimation errors and system overhead.

Future Work

- Joint learning of the port selection and channel estimation steps.
- Exploration of other lightweight models (like LNNs) for on-device compute.
- Application to newer standards (NR-V2X/6G) and ISAC use-cases.

Thank You!

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