Echo State Network for Turbulence-Induced Fading Channel Prediction in Free-Space Optical Systems

Tinh V. Nguyen, Hoang D. Le, and Anh T. Pham

Computer Communications Lab.,
The University of Aizu, Japan

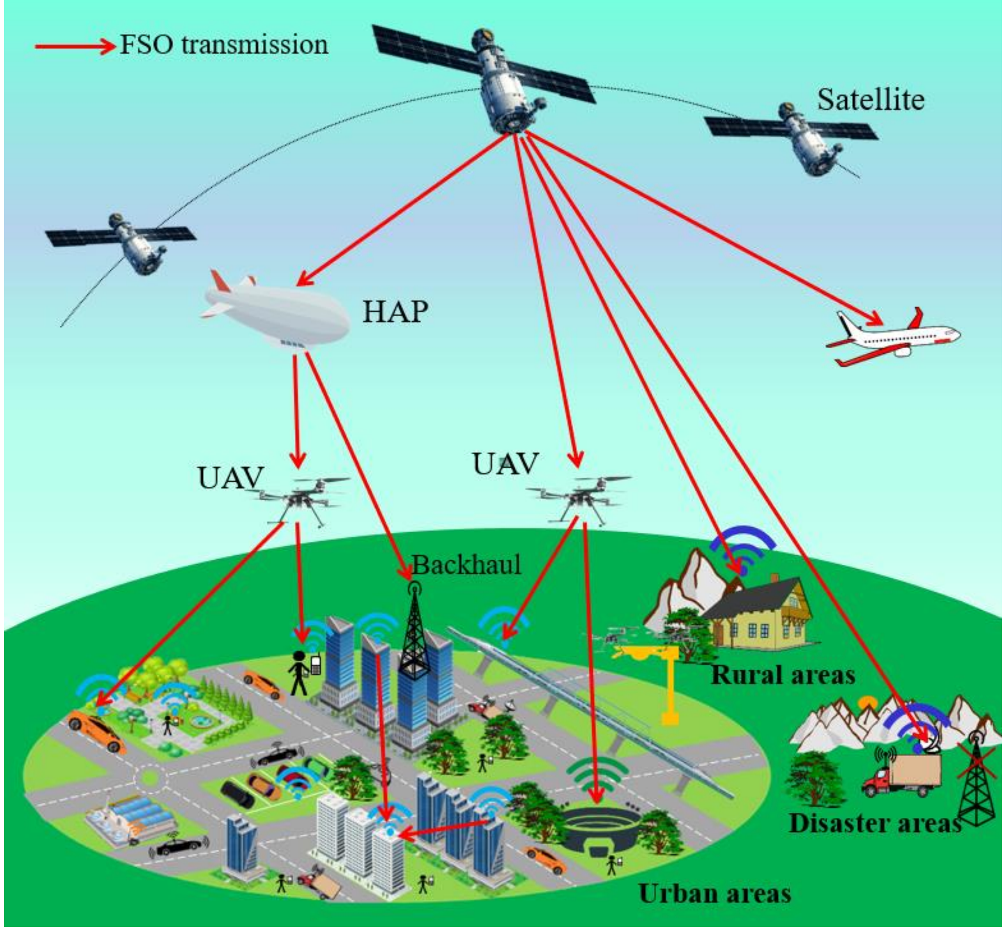
Outline

- Introduction
  - Free-Space Optics (FSO) and Applications
  - Critical Issues and Challenges
  - Possible Solutions and Motivation
- Channel Data and Prediction Model
  - ESN Prediction Model
  - Turbulence Channel Data Analysis
- Performance Analysis and Results
- Conclusions

Introduction

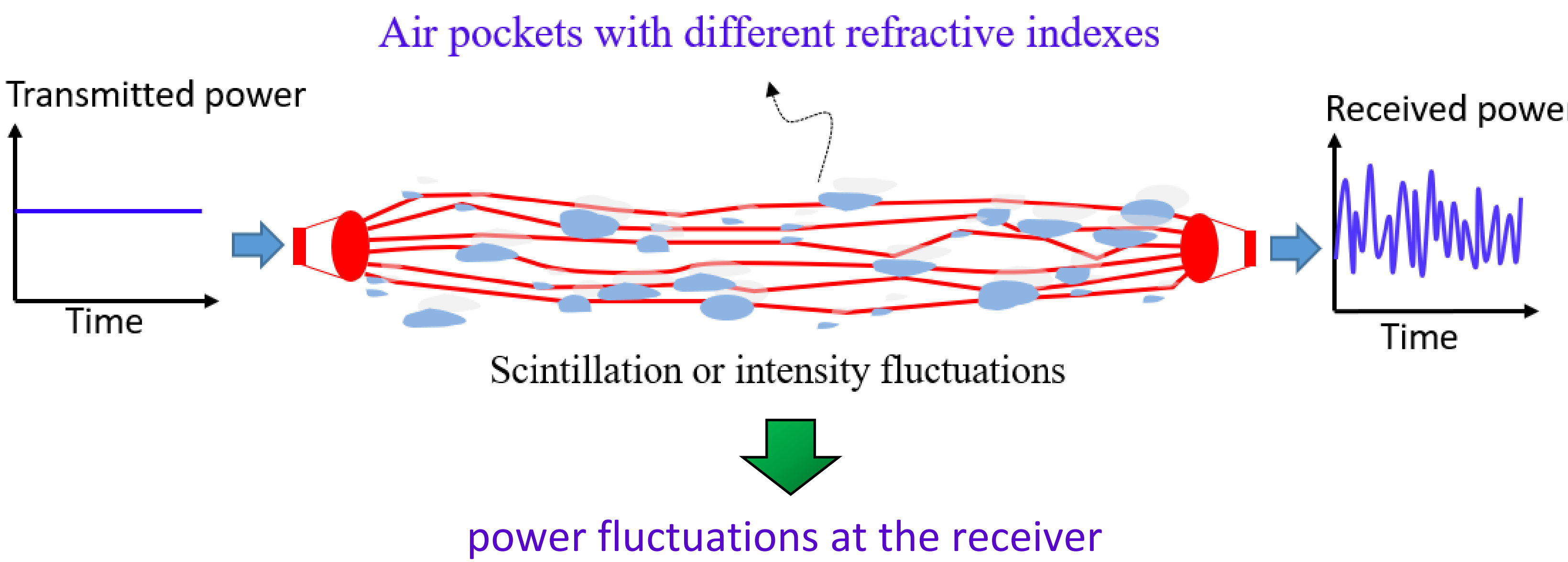
Free-Space Optics (FSO) and Applications

- FSO is a line-of-sight technology using infrared frequency bands for data transmission in free space.
  - Terrestrial systems
  - Space/satellite systems
- Benefits:
  - Large bandwidth, high-speed connections
  - High level of security, immunity to electromagnetic interference
- Applications:
  - Fronthaul/backhaul networks
  - Post-disaster emergency communications
  - Internet of vehicles



Critical Issues and Challenges (1)

- Critical issue: FSO link is sensitive to atmospheric turbulence
  - Inhomogeneity in temperature and pressure along the propagation path causes scintillation effects



*→ Accurate **channel state information (CSI)** at the transmitter is crucial for various mitigation techniques such as adaptive rate/power and hybrid FSO/RF schemes*

Critical Issues and Challenges (2)

- Channel state information (CSI)
  - Describes the current turbulence channel conditions
  - Is estimated at the receiver and fed back to the transmitter

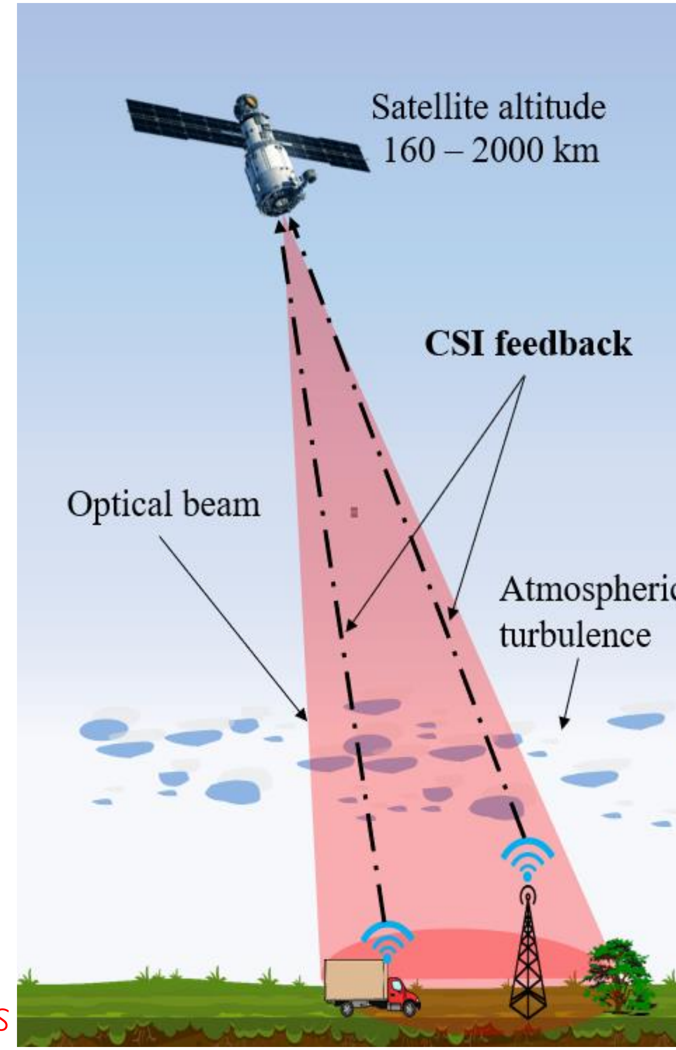
→ The transmitter can adaptively choose proper parameters/settings to guarantee the quality of service, e.g., target BER

- Challenge: the CSI tends to be outdated
  - Due to long feedback distance (up to thousands of kilometers)

→ The feedback time may be longer than the coherence time of the channel

→ The CSI received at the transmitter does not describe the current but the past channel conditions

→ An efficient channel prediction scheme for FSO systems is required



Literature Review: Possible Solutions

- The key idea is to forecast future CSI with a time span that counteracts the induced feedback delay
- Two main approaches:

  1) Statistical prediction 2) Artificial intelligence/machine learning (AIML) prediction

Channel Prediction Schemes

Statistical Prediction

- Auto-regressive (AR)
- Parametric model (PM)

→ Offers a poor accuracy as the modeling is fossilized

AIML Prediction

- Sparse Bayesian linear regression (SBLR)
- Support vector machine (SVM)
- Recurrent neural network (RNN)
- …

→ Offers an excellent potential thanks to its data-driven nature

→ We focus on AIML approach for FSO channel prediction

Motivation

- AIML-based prediction models have been widely applied for radio frequency (RF) systems.

  → They have not been studied for FSO channel prediction, where channels are entirely different from the RF ones.

- Among AIML-based prediction schemes, RNN is famous for its short-term memory capacity.

  → This is especially suitable for processing data sequences in channel prediction.

- Echo state network (ESN), a form of RNN, can randomly construct the hidden layer and leverage a simple linear regression algorithm to train the output layer.

  → It can effectively overcome the common drawbacks of conventional RNNs.

➡ ***With the benefit of a simple structure yet high efficiency, the ESN is a promising candidate for turbulence channel prediction in FSO systems***

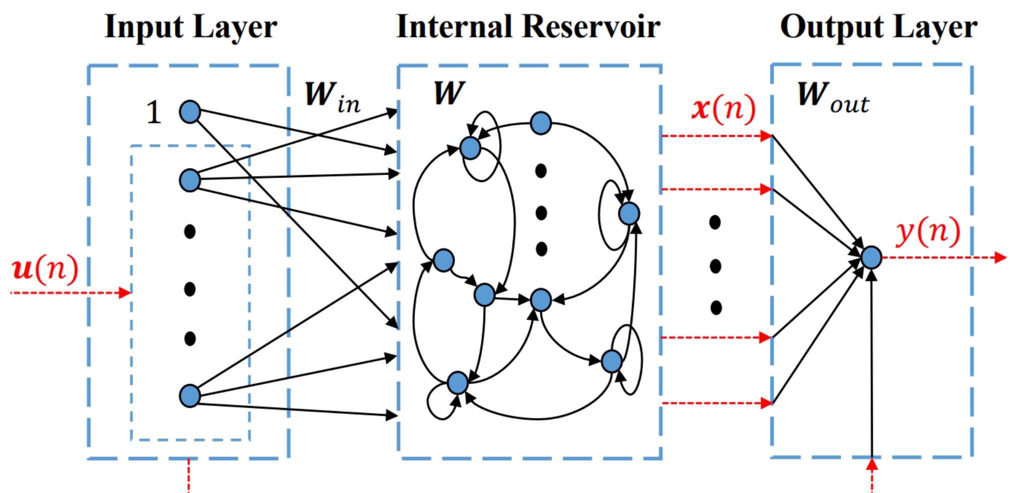
Our Purpose

We employ the ESN and analyze the prediction performance of the ESN model for turbulence-induced fading channels in FSO systems

Channel Data and Prediction Model

ESN Prediction Model (1)

- ESN model has a simple structure
  - Three layers:
    - an input layer [1; $\boldsymbol{u}(n)$] with (M+1) neurons
    - a hidden layer (reservoir) $\boldsymbol{x}(n)$ with N neurons
    - a single-neuron output layer $y(n)$



  - $\boldsymbol{W}_{in}$ and $\boldsymbol{W}$ are the input weight and internal weight matrixes

→ By storing historical information in its internal state, ESN performs enormous potential in time-series prediction

ESN Prediction Model (2)

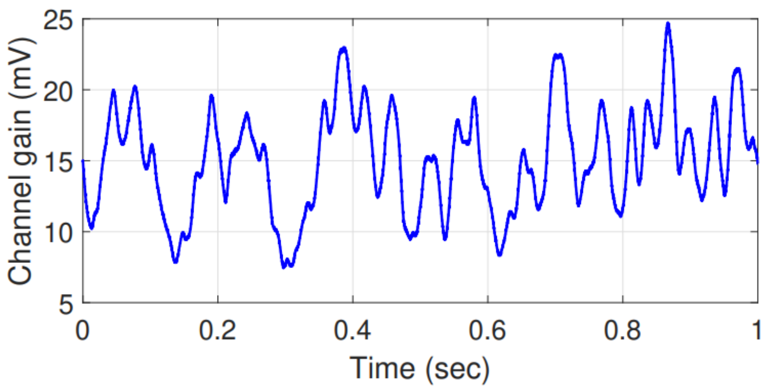
- Operations
  - $\boldsymbol{W}_{in}$ and $\boldsymbol{W}$ are randomly generated, the readout weights $\boldsymbol{W}_{out}$ are trained by using ridge regression
  - At discrete time $\boldsymbol{n}$, $\boldsymbol{M}$ channel gain samples are regarded as input data $\boldsymbol{u}(\boldsymbol{n})$, while output is the predicted channel gain $\boldsymbol{y}(\boldsymbol{n})$ at the next time period
  - The typical updated and output equations are defined as:

$$\tilde{\boldsymbol{x}}(n) = \tanh\left(\boldsymbol{W}_{in}[1; \boldsymbol{u}(n)] + \boldsymbol{W}\boldsymbol{x}(n-1)\right),$$
$$\boldsymbol{x}(n) = (1-\alpha)\boldsymbol{x}(n-1) + \alpha\tilde{\boldsymbol{x}}(n),$$
$$y(n) = \boldsymbol{W}_{out}\left[1; \boldsymbol{u}(n); \boldsymbol{x}(n)\right],$$

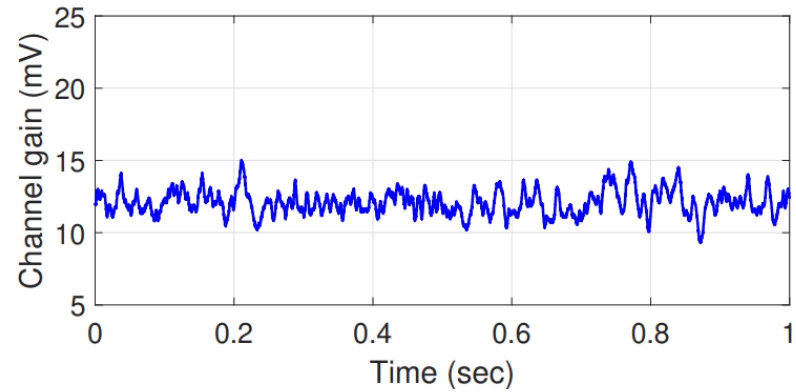
where $\tilde{x}(n)$ is the updated state of $x(n)$, α is the leaking rate, and $[\cdot;\cdot]$ stands for vertical matrix concatenation

Turbulence Channel Data Analysis

- We use the FSO channel data obtained from [1] for training and testing the model.



SI = 0.0594 (higher SI – stronger turbulence)



SI = 0.0051 (lower SI – weaker turbulence)

- The scintillation index (SI) indicates the strength of turbulence conditions.
- Given the total data sample N_h, SI is determined based on the channel gain h

$$\mathrm{SI} = \frac{\langle h^2 \rangle - \langle h \rangle^2}{\langle h \rangle^2}, \text{ where } \langle h \rangle = \frac{1}{N_h} \sum_{i=1}^{N_h} h_i.$$

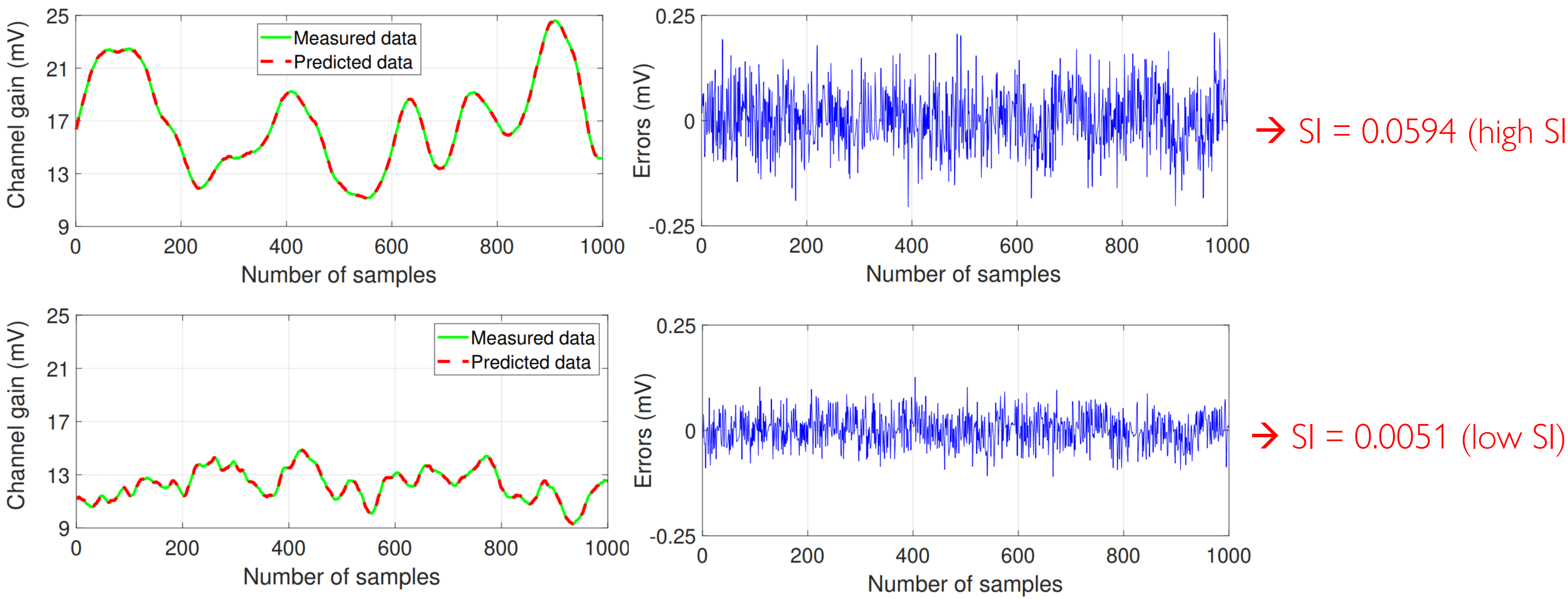
➔ *Turbulence affects greatly on FSO channels.*

[1] 2012. IEEE/OSA J. Optical Commun. Netw. *"Channel Measurement and Markov Modeling of an Urban Free-space Optical Link"*

Performance Analysis and Results

Prediction Performance (1)

- We evaluate the prediction performance of ESN model in different turbulence channel conditions

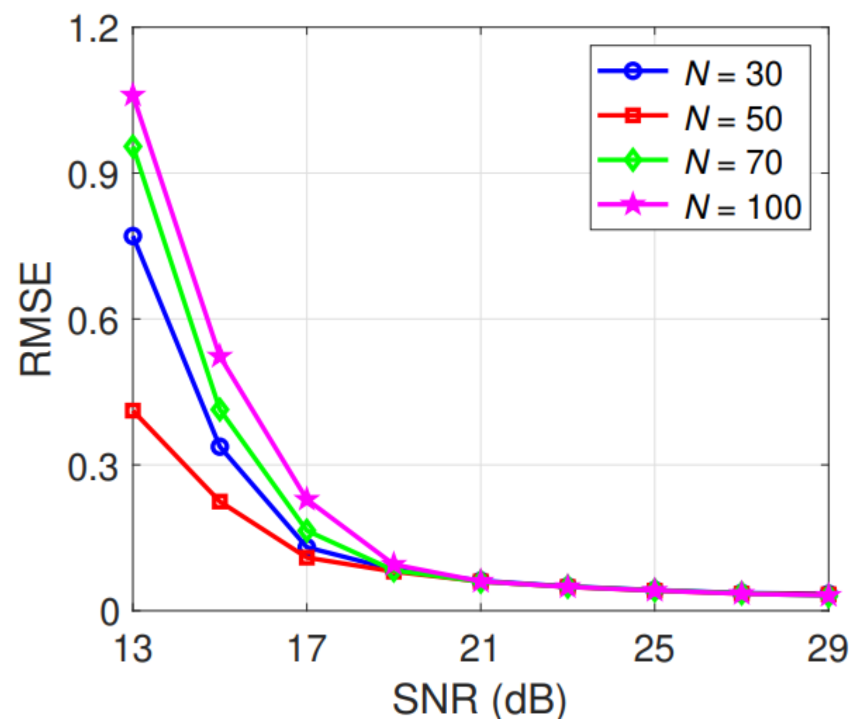


The predicted curves follow the ideal ones closely with low errors.

➔ *ESN has excellent prediction performance over a wide range of turbulence conditions.*

Prediction Performance (2)

- We analyze the prediction performance in terms of signal-to-noise ratios (SNR) for different reservoir sizes.
  - RMSE decreases for higher SNR values.
  - The reservoir size of 50 neurons offers the highest prediction performance. When the reservoir size increases, the accuracy decreases since the model is saturated and overfitting occurs.



Performance Comparison

- We highlight the effectiveness of the ESN model by comparing it with conventional CSI prediction models

  1) Auto-Regressive (AR) – *Statistical prediction approach*

  2) Support Vector Machine (SVM) – *AI/ML prediction approach*

We see that

- ESN model offers the lowest error evaluation, while the AR model has the worst performance.
- SI value increases, the accuracy decreases.

➔ The ESN outperforms AR and SVM models and the performance depends strongly on the current turbulence states.

Data	Model	RMSE	NRMSE	MAPE	SMAPE
SI = 0.0051	AR	0.69571	0.59710	0.04522	0.04525
	SVM	0.11548	0.09885	0.00673	0.00670
	ESN	0.03686	0.03171	0.00242	0.00242
SI = 0.0594	AR	0.98256	0.24908	0.05947	0.05828
	SVM	0.38435	0.10955	0.00694	0.00706
	ESN	0.06843	0.01948	0.00334	0.00334

Conclusions

- We presented an AIML-based ESN model for turbulence-induced fading channel prediction in FSO systems.
- Remarkable observations from results
  - The ESN model offers excellent prediction performance in FSO systems.
  - The ESN model outperforms the classical AR and SVM models in terms of accuracy.
  - The prediction performance depends greatly on the turbulence channel conditions.
- Future work
  - Employ the model to investigate the PHY/link-layer performance of FSO-based satellite communications using rate adaptation/hybrid FSO/RF schemes.

Thank you for your listening!