# A PAM-4 behavioral model using Laguerre-Volterra feed forward neural network and its implementation in IBIS-AMI

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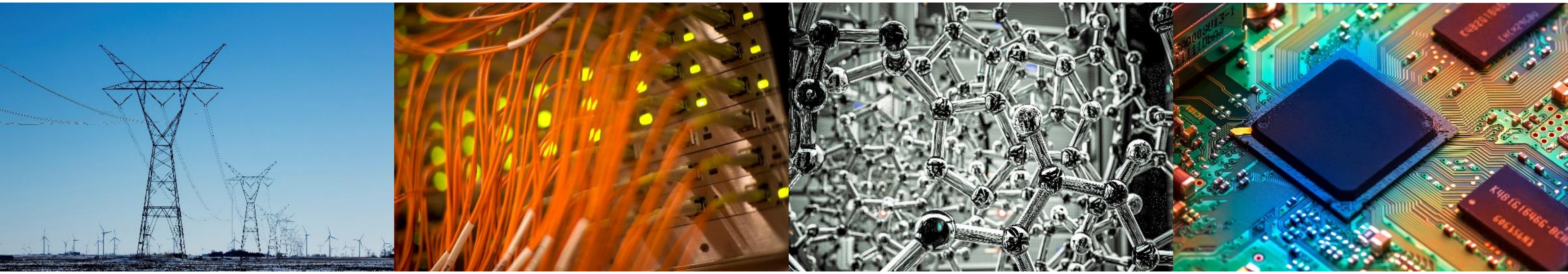

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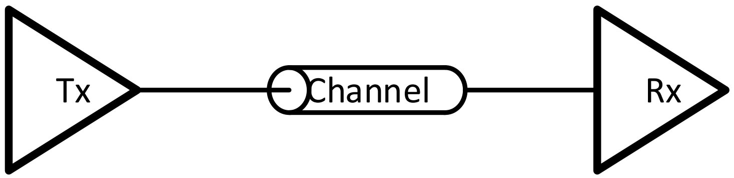
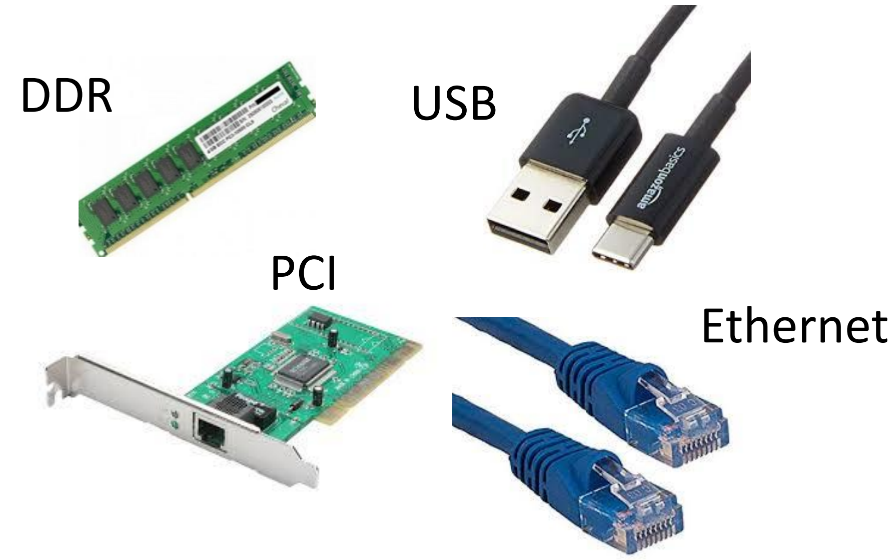
# Outline

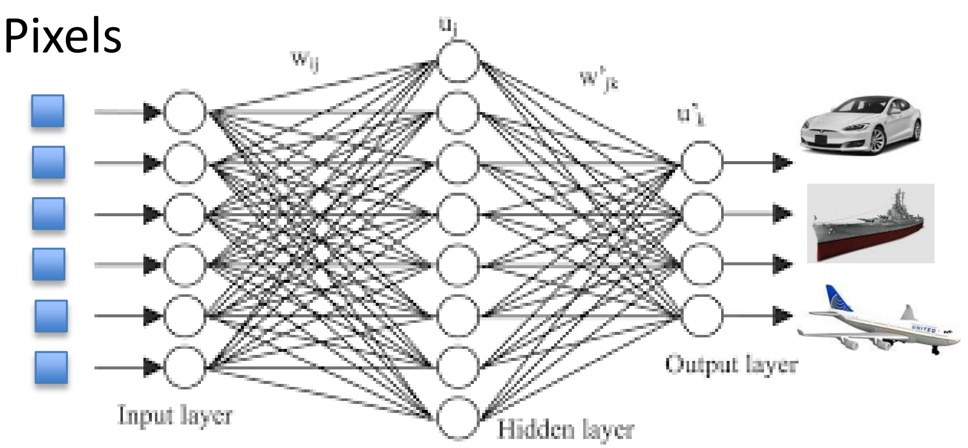
- Introduction and motivation
- Volterra series and Laguerre-Volterra feed forward neural network (LVFFN)
- PAM-4 behavior modeling using LVFFN
- IBIS-AMI model implementation and ezAMI software
- Summary

# Introduction

- High speed link technology
  - Non-Return-to-Zero (NRZ)
  - Pulse Modulation 4-level (PAM-4)
- Behavioral model
  - A compact mathematical model
  - Fast and accurate
  - IP protection
- Artificial neural network
  - A mathematical mapping of input to output
  - FFN, CNN, RNN

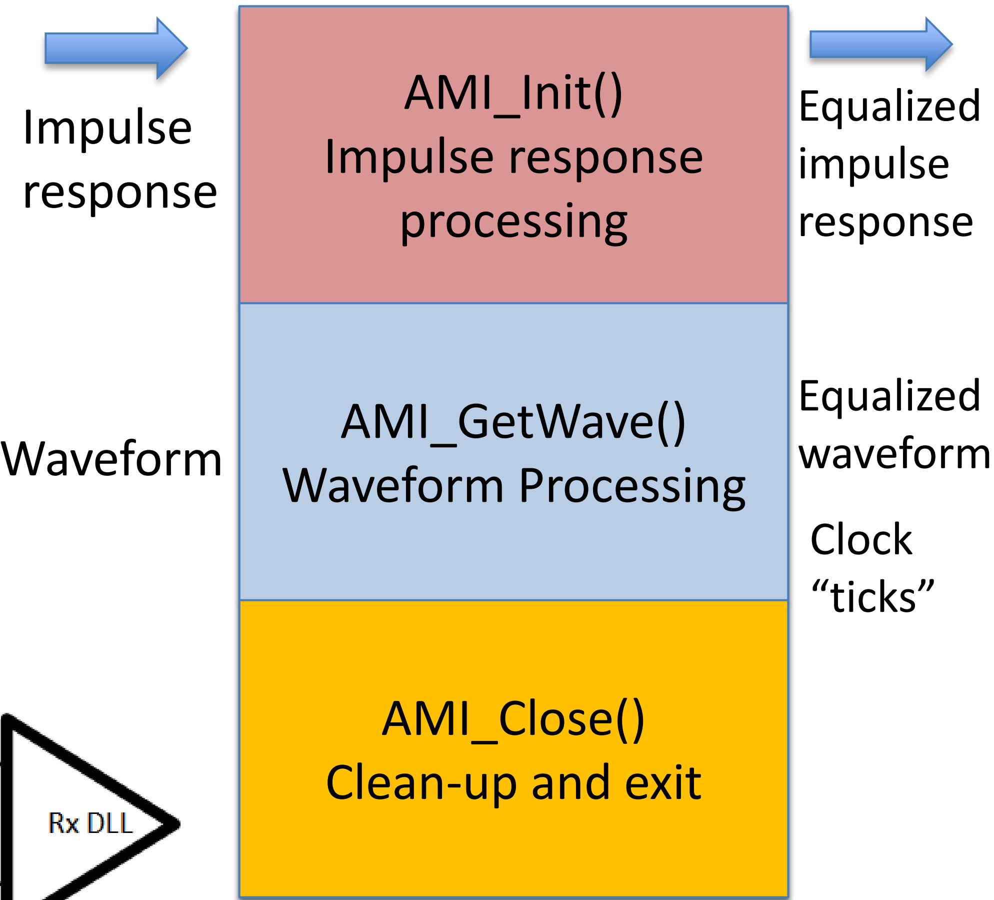


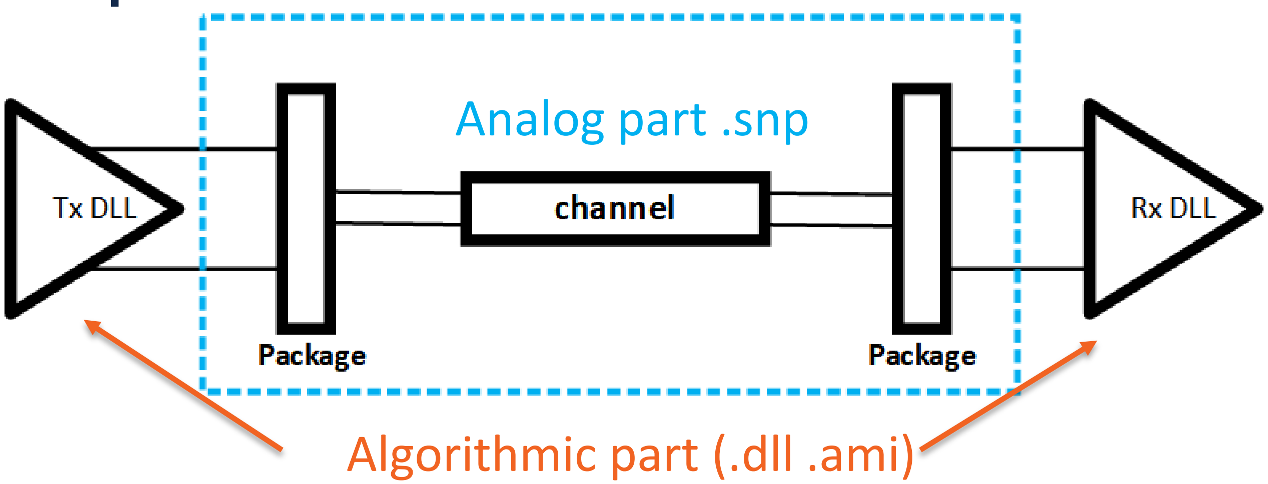



# IBIS-AMI Model Basics

- An interface to model SerDes IP in commercial EDA simulators
- Interoperable, flexible, high performance, and IP protection



# Motivation and focus of this work

- High demand for rapid data transmission.

  100Gb/s -> 400Gb/s
- Simulation and validation are desirable to cut development time and cost
  - A high-performance model is the key
- Behavioral model using machine learning is emerging
  - Large model size
  - Lack of interoperability and transportability
- High speed link behavioral model development
  - A machine learning behavioral model
  - Take nonlinearity into accountable
  - Fast and accurate
- IBIS-AMI model generation
  - Enhance model interoperability and transportability
  - Compatible with commercial circuit simulator
- IBIS-AMI model generation software

# Volterra Series

- A versatile model for nonlinear systems with memory

$$\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{y}_0 + \sum_{\boldsymbol{n}=1}^{\infty} \boldsymbol{y}_{\boldsymbol{n}}(\boldsymbol{t})$$

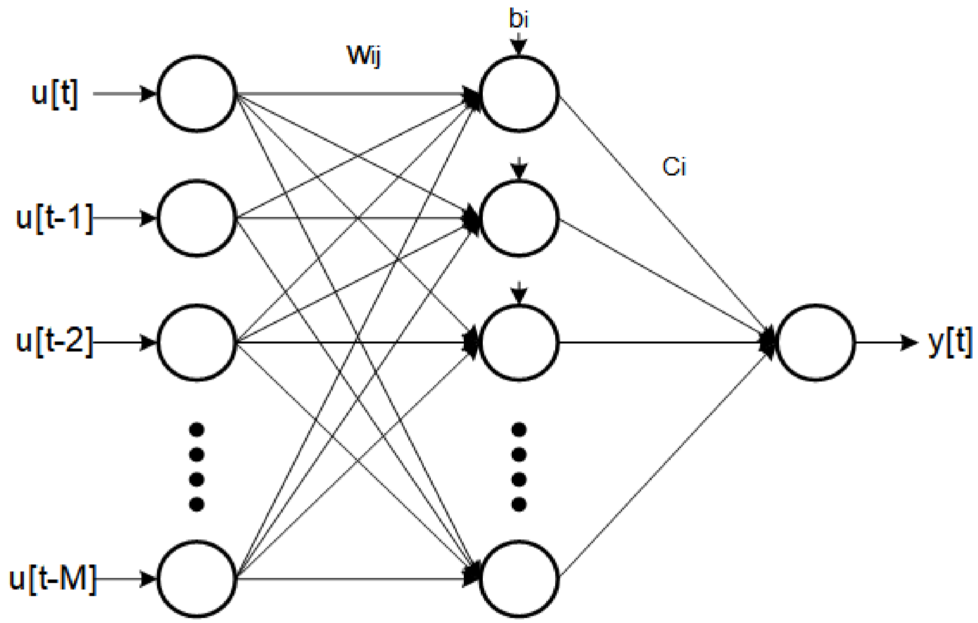
$$\boldsymbol{y}_{\boldsymbol{n}}(\boldsymbol{t}) = \int_{-\infty}^{+\infty} \dots \int_{-\infty}^{+\infty} \boldsymbol{h}_{\boldsymbol{n}}(\boldsymbol{\tau}_1, \boldsymbol{\tau}_2, \dots, \boldsymbol{\tau}_{\boldsymbol{n}})\boldsymbol{u}(\boldsymbol{t}-\boldsymbol{\tau}_1)\boldsymbol{u}(\boldsymbol{t}-\boldsymbol{\tau}_2)\dots\boldsymbol{u}(\boldsymbol{t}-\boldsymbol{\tau}_{\boldsymbol{n}})\boldsymbol{d}\boldsymbol{\tau}_1\boldsymbol{d}\boldsymbol{\tau}_2\dots\boldsymbol{d}\boldsymbol{\tau}_{\boldsymbol{n}}$$

In discrete time

$$\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{h}_0 + \sum_{\boldsymbol{\tau}_1=0}^{\infty} \boldsymbol{h}_1(\boldsymbol{\tau}_1)\boldsymbol{u}(\boldsymbol{t}-\boldsymbol{\tau}_1) + \sum_{\boldsymbol{\tau}_1=0}^{\infty}\sum_{\boldsymbol{\tau}_2=0}^{\infty} \boldsymbol{h}_2(\boldsymbol{\tau}_1, \boldsymbol{\tau}_2)\,\boldsymbol{u}(\boldsymbol{t}-\boldsymbol{\tau}_1)\boldsymbol{u}(\boldsymbol{t}-\boldsymbol{\tau}_2) + \cdots$$

$\boldsymbol{h}_0, \boldsymbol{h}_1, \boldsymbol{h}_2, \dots, \boldsymbol{h}_{\boldsymbol{n}}$ are the Volterra kernels

# Monomial Power Series Neural Network




$$y[t] = \sum_{i=1}^{M} c_i \sigma \left( b_i + \sum_{j=1}^{M} w_{ji} u[t-j] \right)$$

$$\boldsymbol{y(t) = h_0 + \sum_{\tau_1=0}^{M} h_1(\tau_1) u(t-\tau_1) +}$$

$$\boldsymbol{\sum_{\tau_1=0}^{M} \sum_{\tau_2=0}^{M} h_2(\tau_1, \tau_2)\, u(t-\tau_1) u(t-\tau_2) + \cdots}$$

$$\boldsymbol{h_0 = \sum_{i=1}^{M} c_i a_{0i}}$$

$$\boldsymbol{h_1(j) = \sum_{i=1}^{M} c_i a_{1i} w_{ji}}$$

$$\boldsymbol{h_2(j,k) = \sum_{i=1}^{M} c_i a_{2i}\, w_{ji} w_{ki}}$$

$$\boldsymbol{h_n(v_1, v_2, \dots, v_n) = \sum_{i=1}^{M} c_i a_{ni}\, w_{ji} w_{ki} \dots\, w_{vni}}$$

<u>X Wang, T Nguyen, J Schutt-Aine, EMC Sapporo & APEMC 2019</u>

<u>T Nguyen , X Wang, J Schutt-Aine, ECTC 2019</u>

# Challenges with Volterra Series

- Large number of parameters when nonlinearity order goes high

Number of Volterra Kernels

M denotes memory length

| | $1^{st}$ order | $2^{nd}$ order | $3^{rd}$ order | $4^{th}$ order |
|---|---|---|---|---|
| M = 10 | 10 | 110 | 1,110 | 11,110 |
| M = 20 | 20 | 420 | 8,420 | 168,420 |
| M = 30 | 30 | 930 | 27,930 | 837,930 |
| M = 40 | 40 | 1,640 | 641,640 | 3,201,640 |

Number of Laguerre Parameters

R denotes the number of Laguerre function for expansion

| | $1^{st}$ order | $2^{nd}$ order | $3^{rd}$ order | $4^{th}$ order |
|---|---|---|---|---|
| R = 2 | 2 | 6 | 14 | 30 |
| R = 3 | 3 | 12 | 39 | 120 |
| R = 4 | 4 | 20 | 84 | 340 |
| R = 5 | 5 | 30 | 155 | 780 |

# Laguerre-Volterra Feed Forward Neural Network (LVFFN)

- Reduce dimension through projecting Volterra kernels on finite number of Laguerre Functions

$$h(t) = \sum_{r=1}^{R} \theta_r \varphi_r(t)$$

- Typically, $R$ is much smaller compared to the memory length M

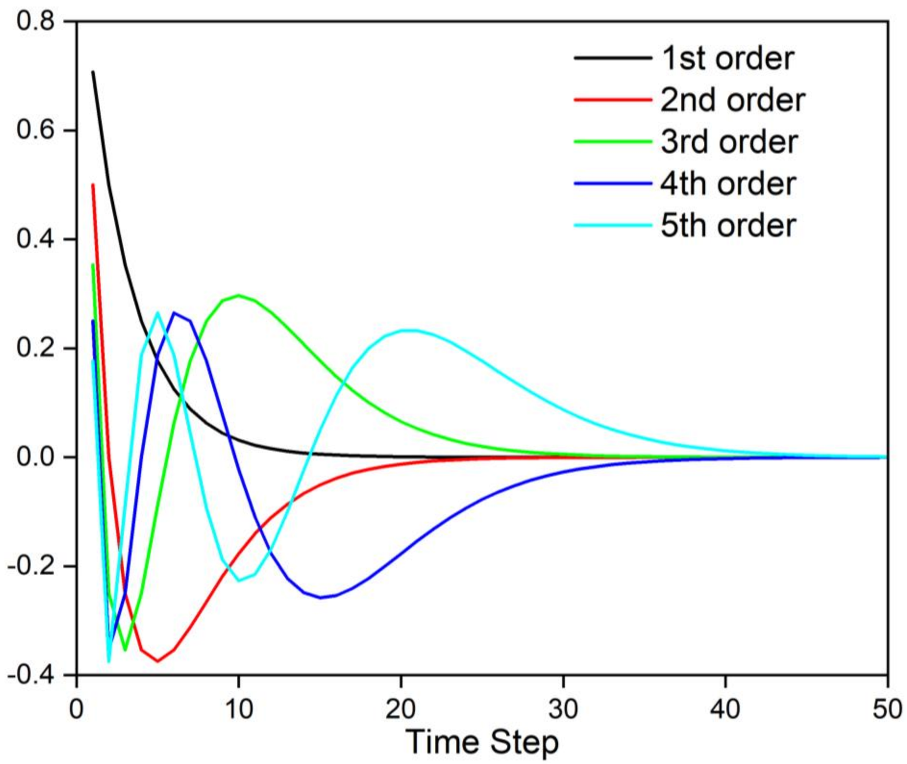
# Discrete Time Laguerre Functions

$$\varphi_r(t) = \alpha^{\frac{t-r}{2}}(1-\alpha)^{\frac{1}{2}}\sum_{k=0}^{r}(-1)^k\binom{t}{k}\binom{r}{k}\alpha^{r-k}\,(1-\alpha)^k$$

- Guaranteed to converge at infinity
- Functions are orthogonal basis

$$<\varphi_i,\varphi_j> = \begin{cases} 0 & i \neq j \\ \sigma & i = j \end{cases}$$

- $\alpha$ is the decay factor which takes value (0,1)
- $r$ is the function order



# From Volterra Space to Laguerre Space

## Volterra Series

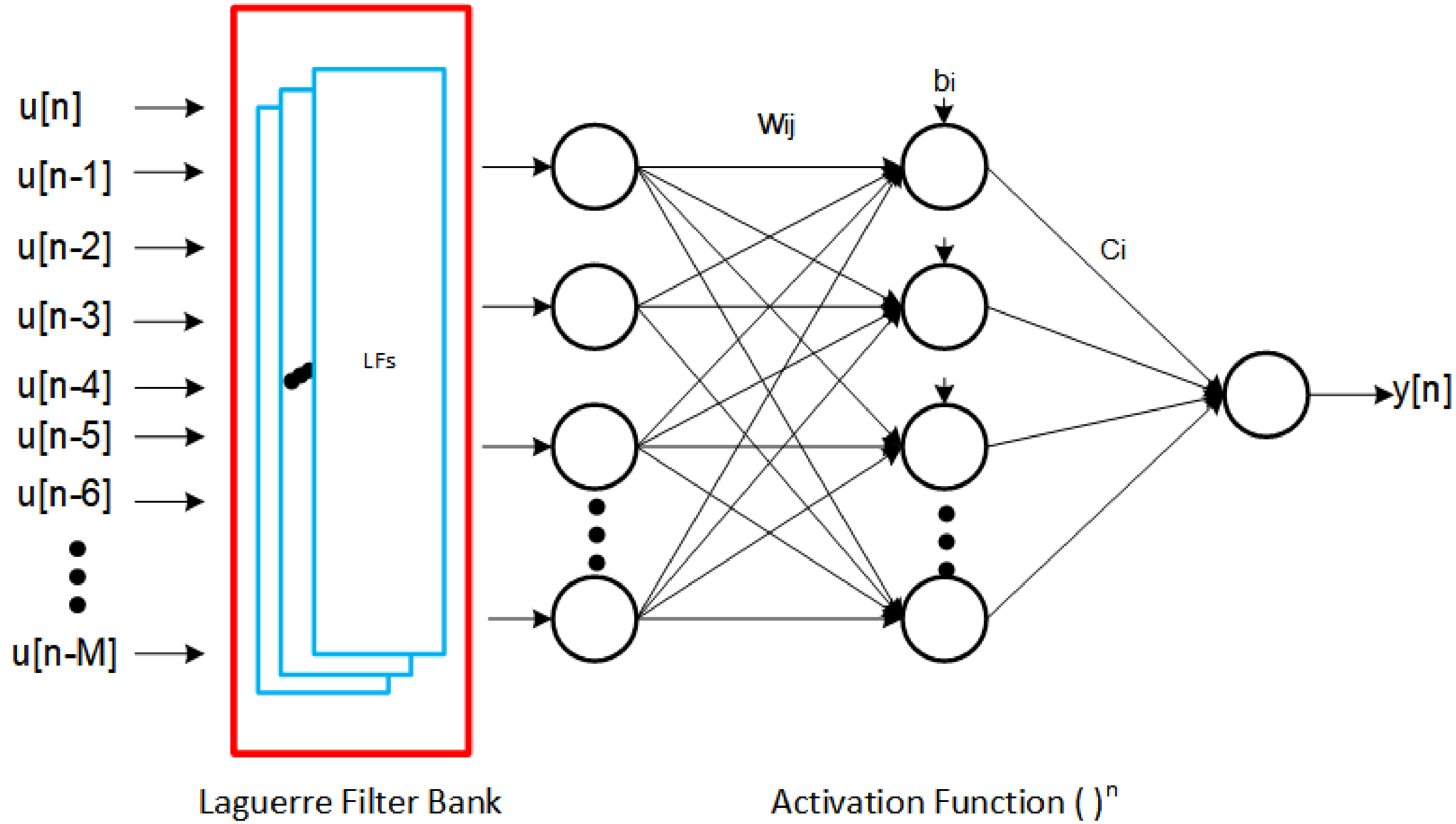
$$y(t) = h_0 + \sum_{\tau_1=0}^{M} h_1(\tau_1)u(t-\tau_1) + \sum_{\tau_1=0}^{M}\sum_{\tau_2=0}^{M} h_2(\tau_1,\tau_2)\,u(t-\tau_1)u(t-\tau_2)$$

$$+\cdots$$

## Laguerre-Volterra model

$$y(t) = \theta_0 + \sum_{r_1=1}^{R} \theta_1(r_1)v_{r_1}(t) + \sum_{r_1=1}^{R}\sum_{r_2=1}^{R} \theta_2(r_1,r_2)v_{r_1}(t)v_{r_2}(t) + \cdots$$

# Identification of Laguerre Coefficients

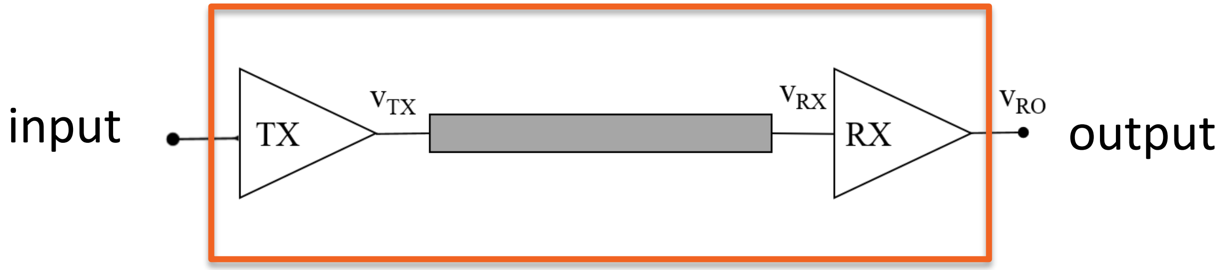


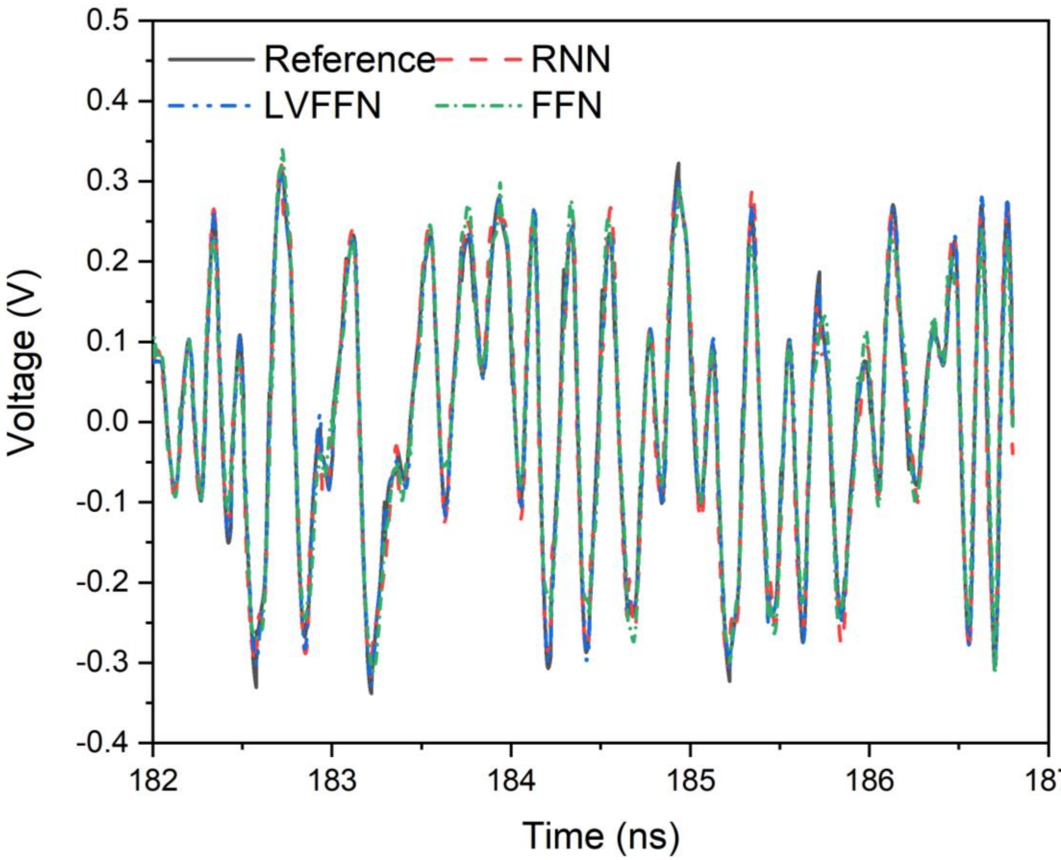

<u>**X Wang, T Nguyen, J Schutt-Aine, TCPMT 2020**</u>

<u>**X Wang, T Nguyen, J Schutt-Aine, LASCAS 2020**</u>

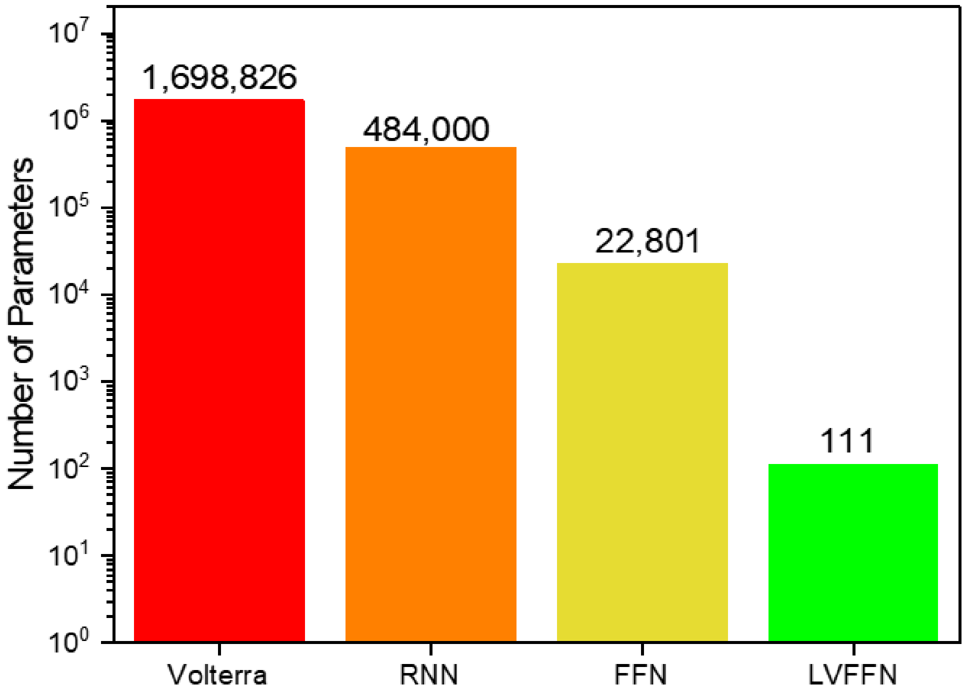
# Modeling PAM-4 system

- LVFFN architecture: one hidden layer with 10 neurons
- FFN architecture: one hidden layer with 150 neurons
- RNN architecture:
  - 100 memory length
  - 6 stacked layers
  - 20 neurons for each layer

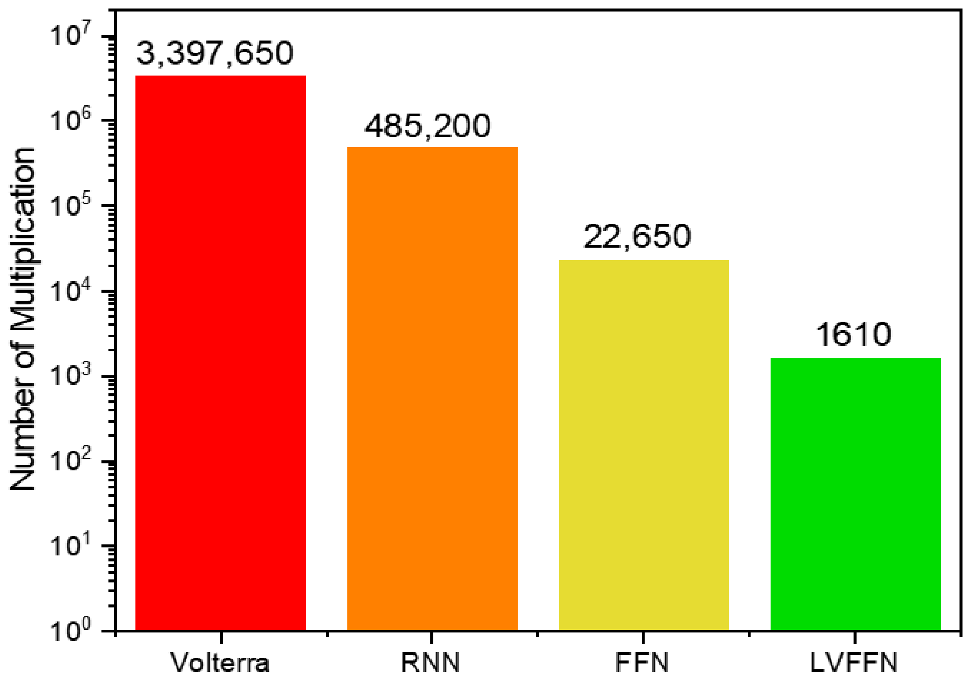


# Model Size Reduction and Computation Efficiency




Model size comparison




Computation efficiency comparison

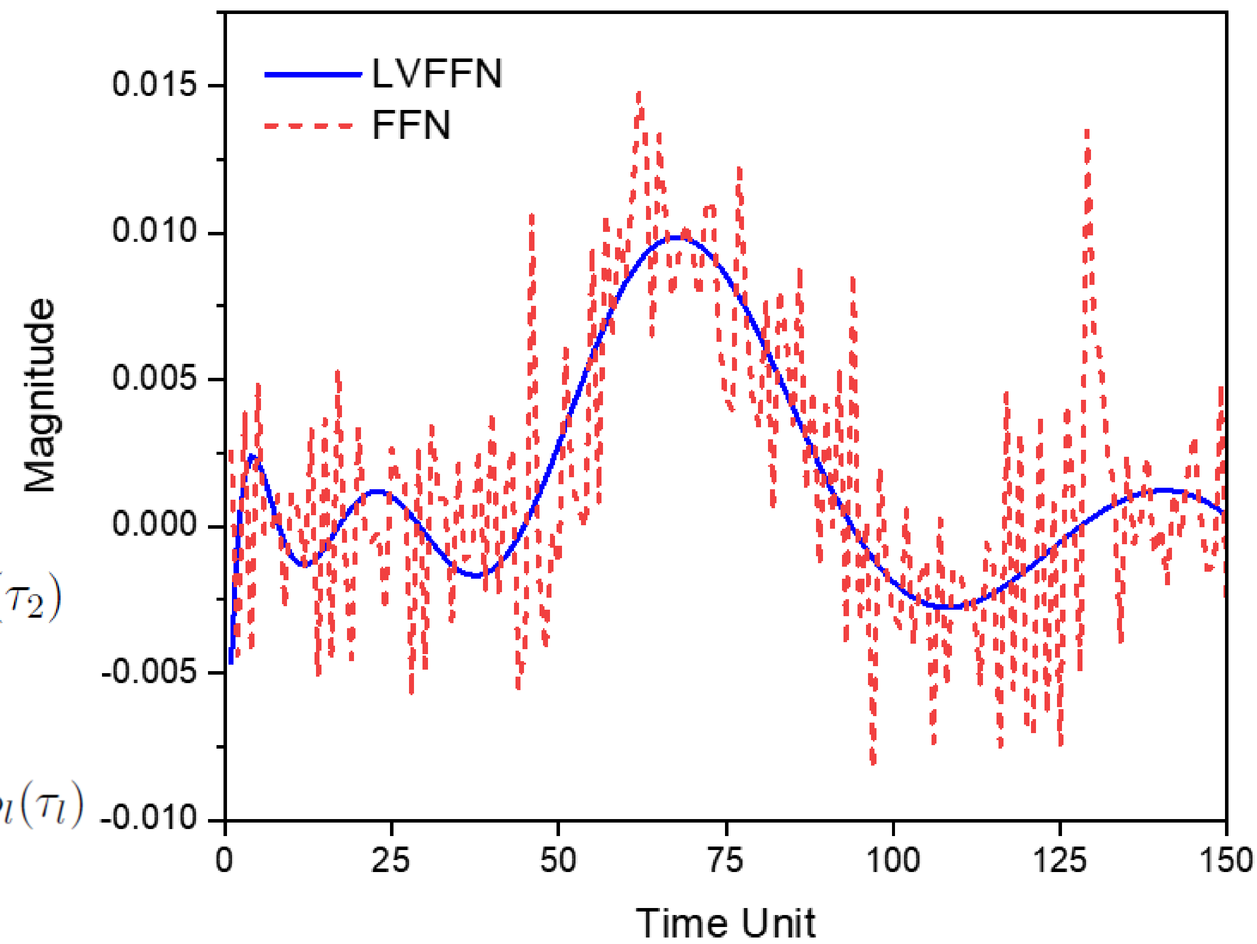
# Volterra Kernel Extraction with LVFFN

$$h_0 = \theta_0$$

$$h_1(\tau) = \sum_{r=1}^{r=R} \theta_r \phi_r(\tau)$$

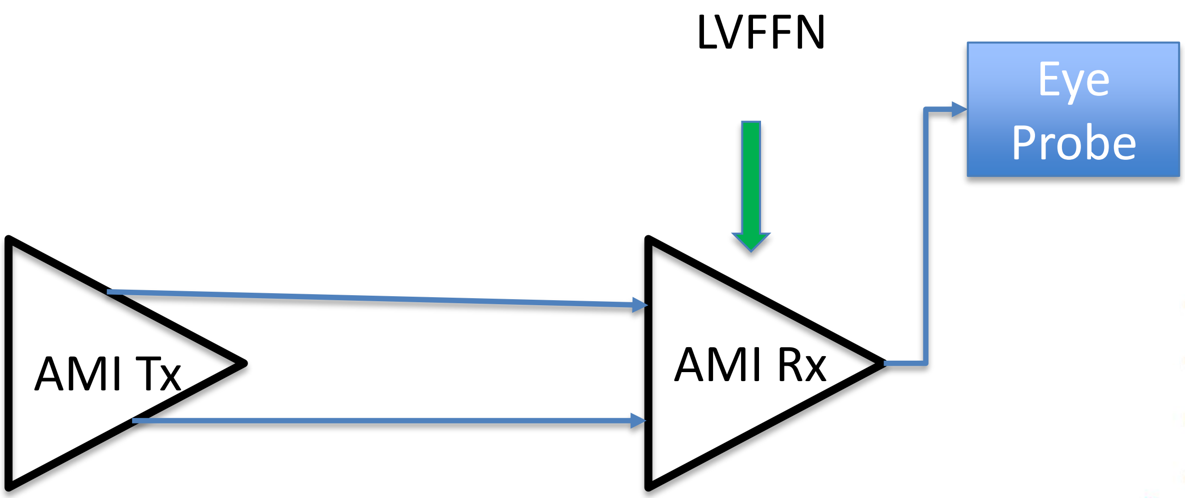
$$h_2(\tau_1, \tau_2) = \sum_{r_1=1}^{r_1=R} \sum_{r_2=1}^{r_2=R} \theta_{r_1,r_2} \phi_{r_1}(\tau_1) \phi_{r_2}(\tau_2)$$

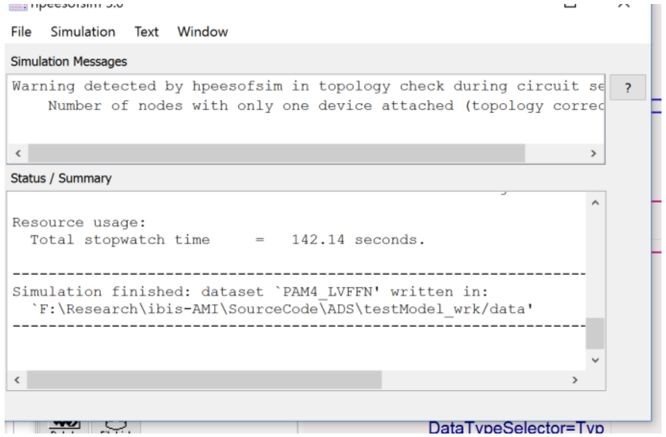
$$h_n(\tau_1, ..., \tau_n) = \sum_{r_1=1}^{r_1=R} ... \sum_{r_n=1}^{r_n=R} \theta_{r_1,...,r_n} \prod_{l=1}^{n} \phi_l(\tau_l)$$

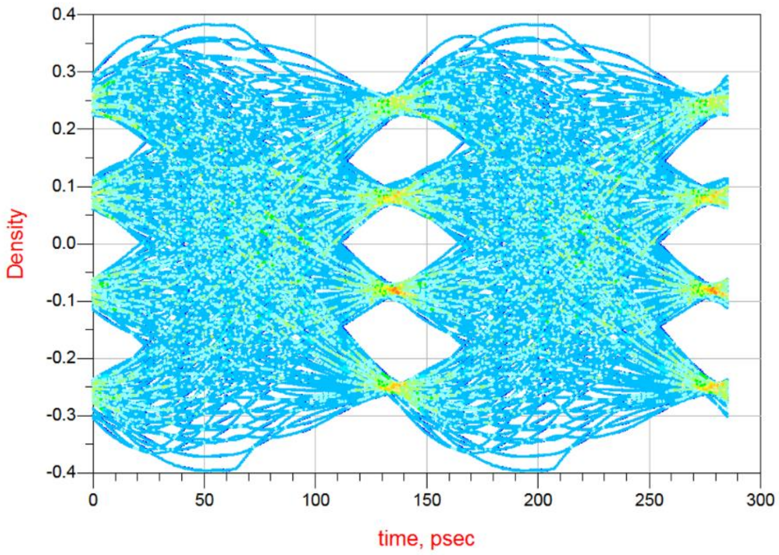


# Implementation in IBIS-AMI

## Simulating 1 million bits takes 142s!

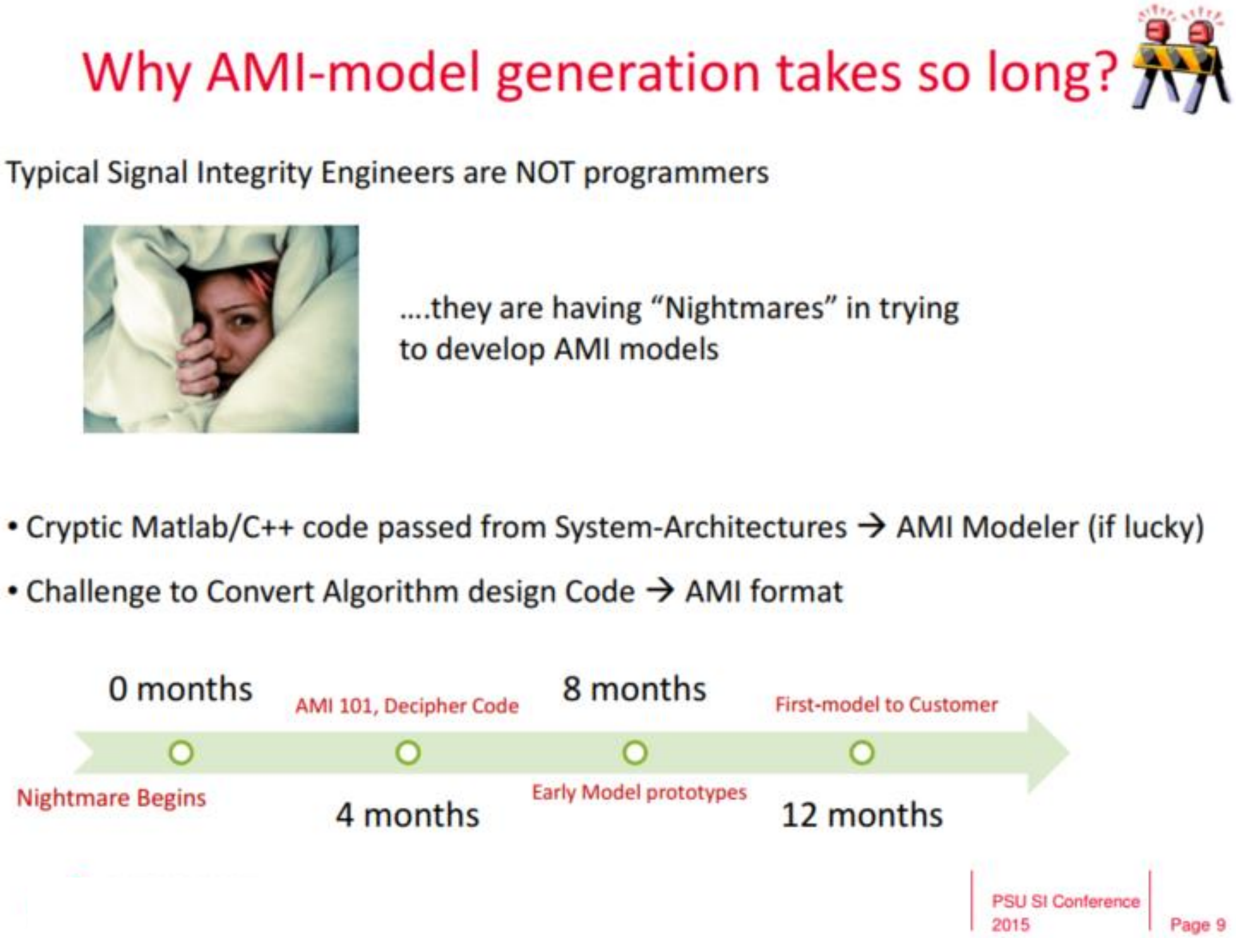


# IBIS-AMI Model Generation

- Model generation requires cross-disciplinary knowledge
- ezAMI software facilitates the model generation

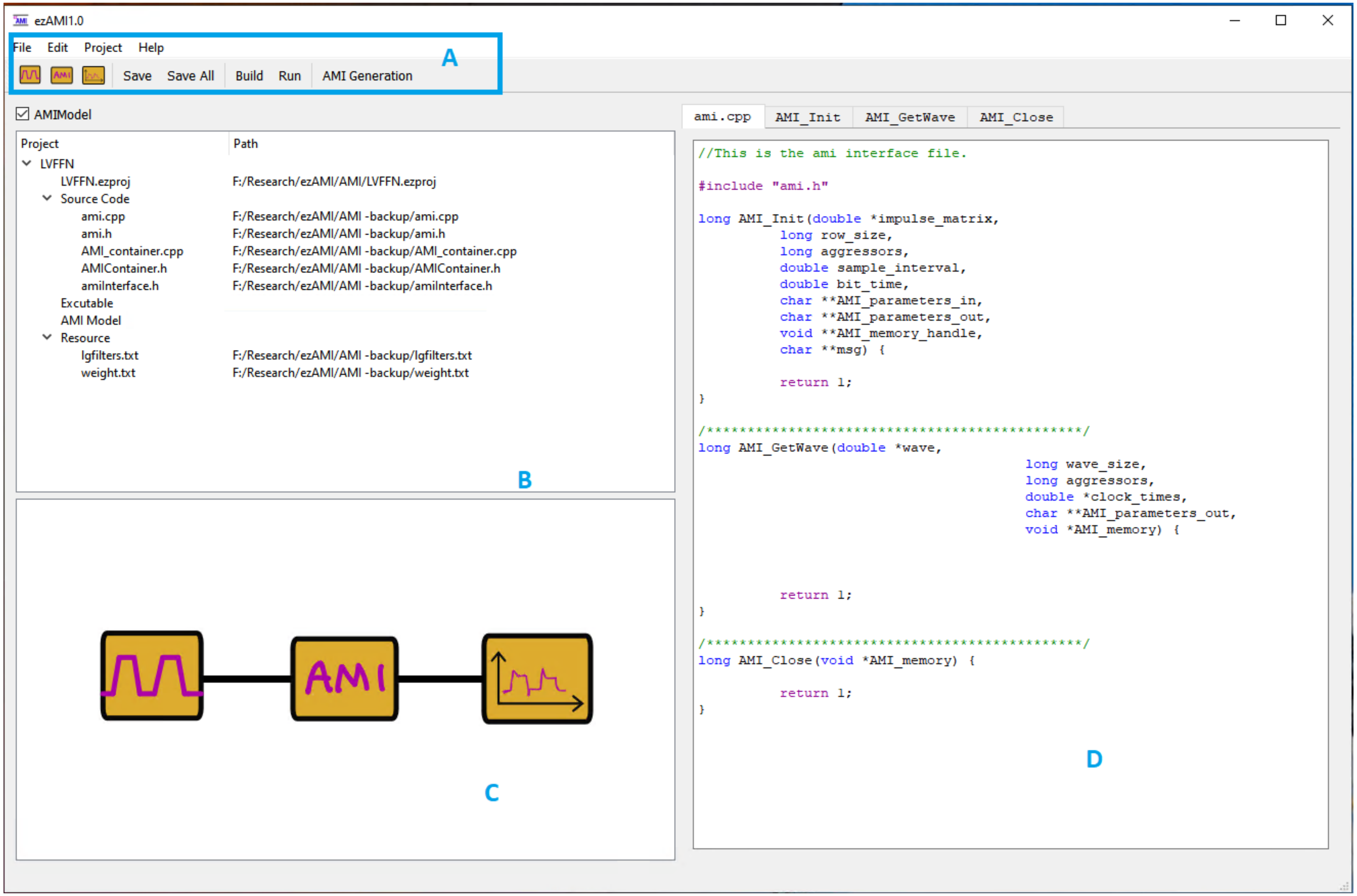



https://ibis.org/summits/jun10/pino.pdf

# ezAMI software

- IBIS-AMI model generator and simulator
- Supports model pre-generation verification
- Allows on-site development and debug
- Supports NRZ and PAM-4 simulation
- Project-based development
- User-friendly GUI system

# Software interface



# Software download links

- https://gitlab.engr.illinois.edu/xinying/ezami
- https://github.com/WXY163/ezAMI
- Installer: https://github.com/WXY163/ezAMI/tree/master/installer
- Tutorial : https://github.com/WXY163/ezAMI/blob/master/documents/toturial.pdf

Quick demo…

# Summary

- Proposed a Laguerre-Volterra feed forward neural network (LVFFN) which can significantly reduce the model size and enhance the computation efficiency for modeling PAM-4 systems
- Implemented the PAM-4 LVFFN model in IBIS-AMI and simulated it in industrial EDA tools
- Developed an IBIS-AMI model generation software ezAMI which can help developing non-traditional SERDES IBIS-AMI model.

# Thank you!