Te Photonic Synapses for Physical Reservoir Computing

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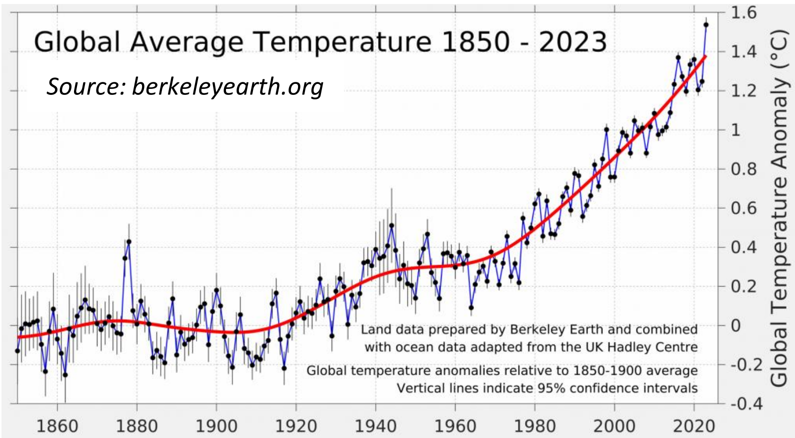
Reference: Hyerin Jo#, Jiseong Jang#, Hyeon Jung Park#, Huigu Lee, Sung Jin An, Jin Pyo Hong*, Mun Seok Jeong*, and Hongseok Oh*, "Physical reservoir computing using tellurium-based gate-tunable artificial photonic synapses", *ACS Nano*, **18**, 44 (2024): 30761–73.

What is Reservoir Computing

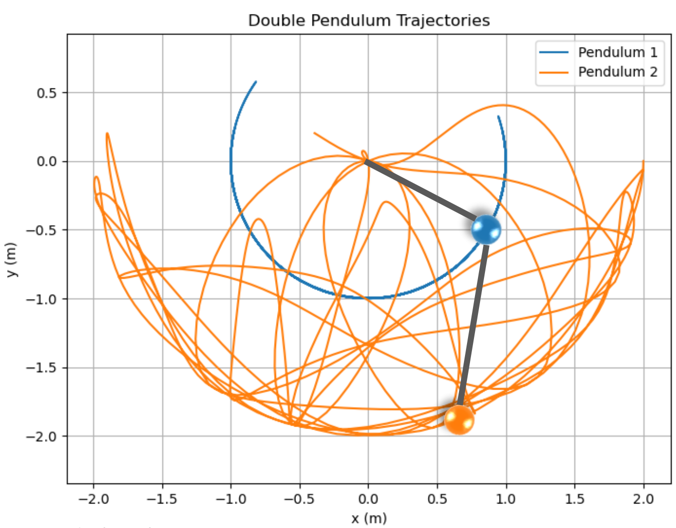
Nonlinear dynamical systems

Natural systems



Social systems

Engineering systems



Code by ChatGPT

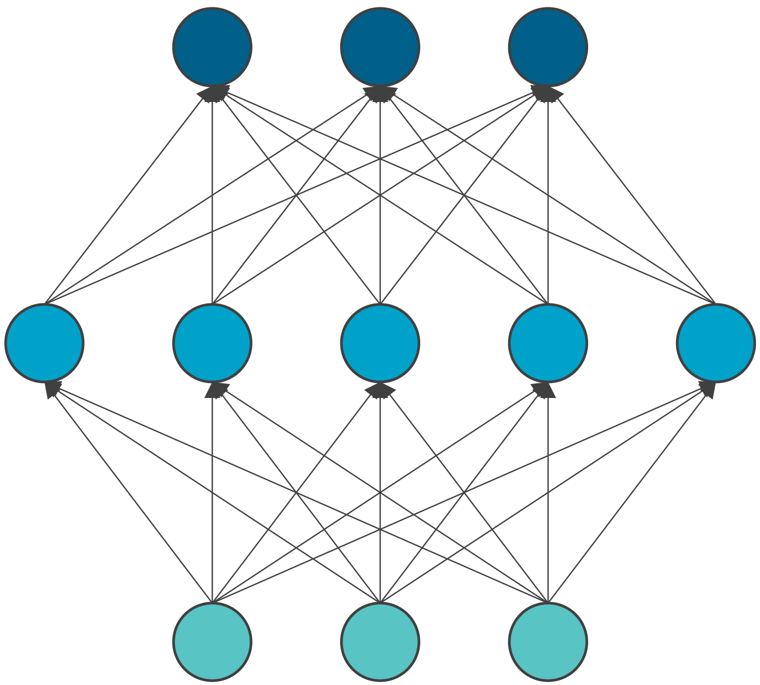
Biological systems

Cardiac rhythms

Source: cardiorhythm.co.za

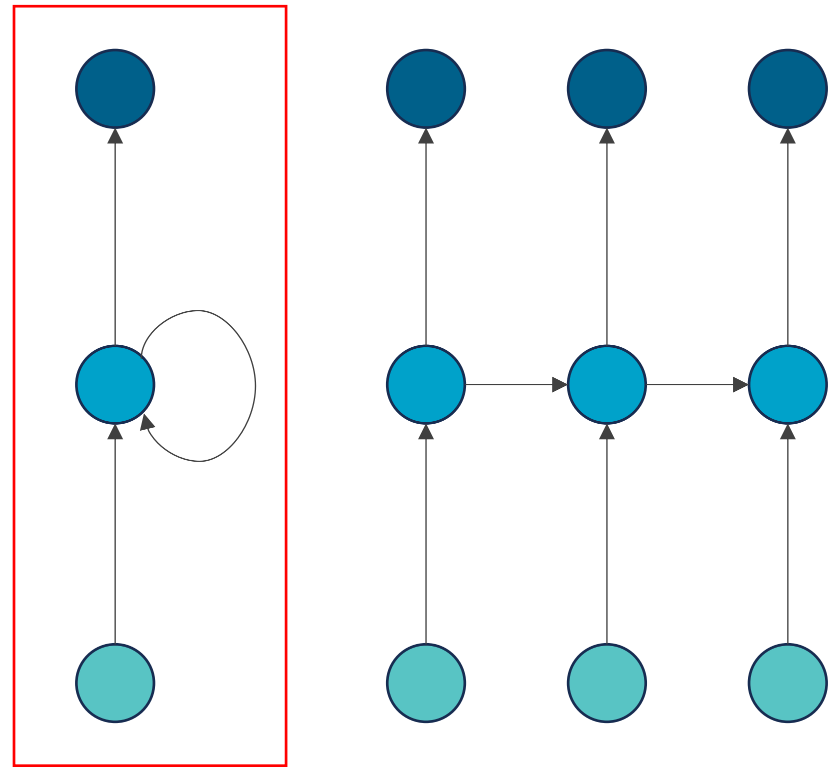
Recurrent Neural Network (RNN)

Feed-Forward Network



- For static input
- Perceptrons are used once for each input

Recurrent Neural Network

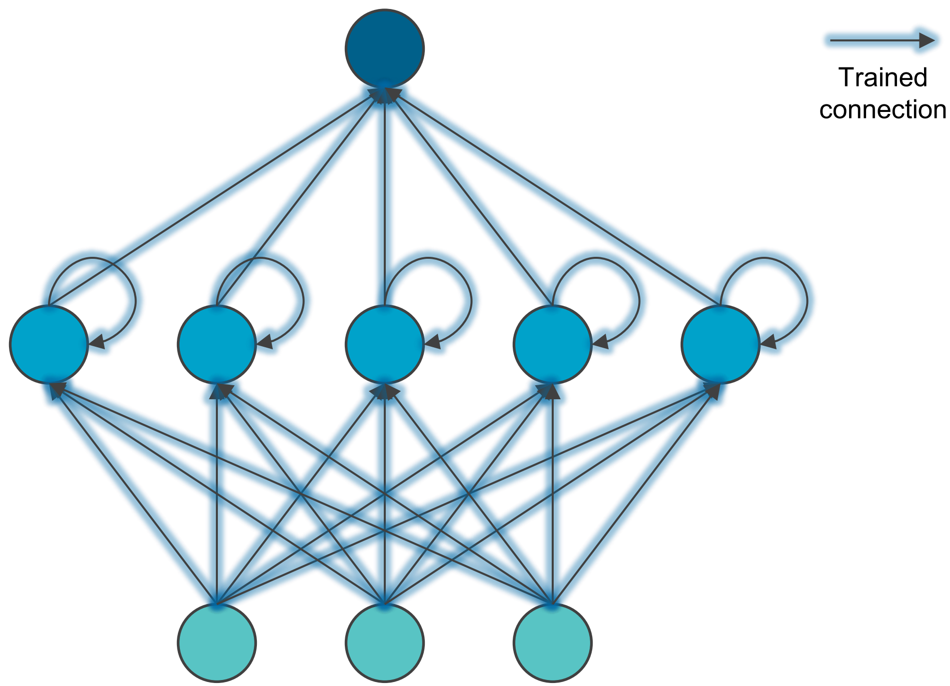


- For dynamic input
- Perceptrons are used repeatedly during the given input
- Output of nodes at ‘n-1’th series becomes input of ‘n’th series

Disadvantages of RNN

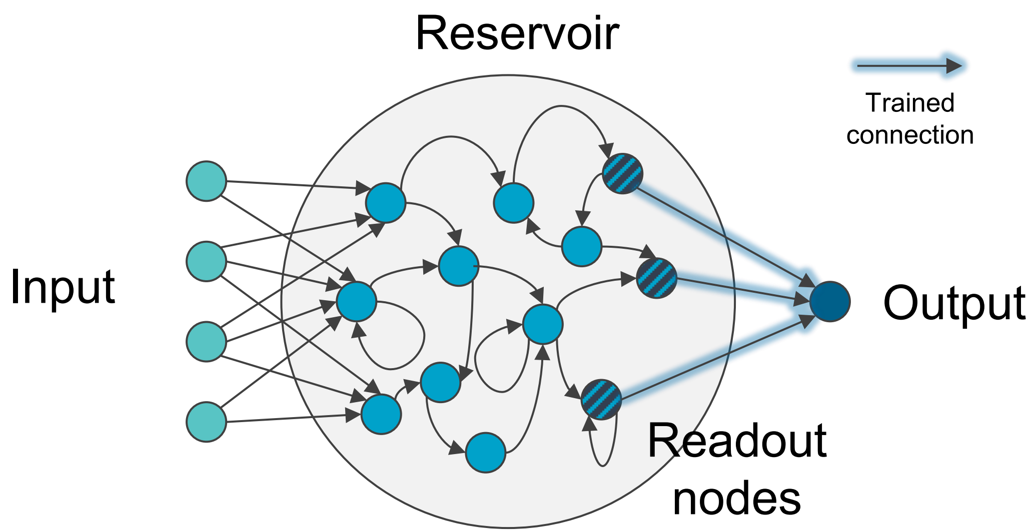
Source: https://iq.opengenus.org/disadvantages-of-rnn/

- Vanishing or exploding gradient problem
- **Slow and complex training procedure**



Reservoir computing

Ref: Lukoševičius, Mantas, and Herbert Jaeger.
Computer Science Review 3, no. 3, 127–49.

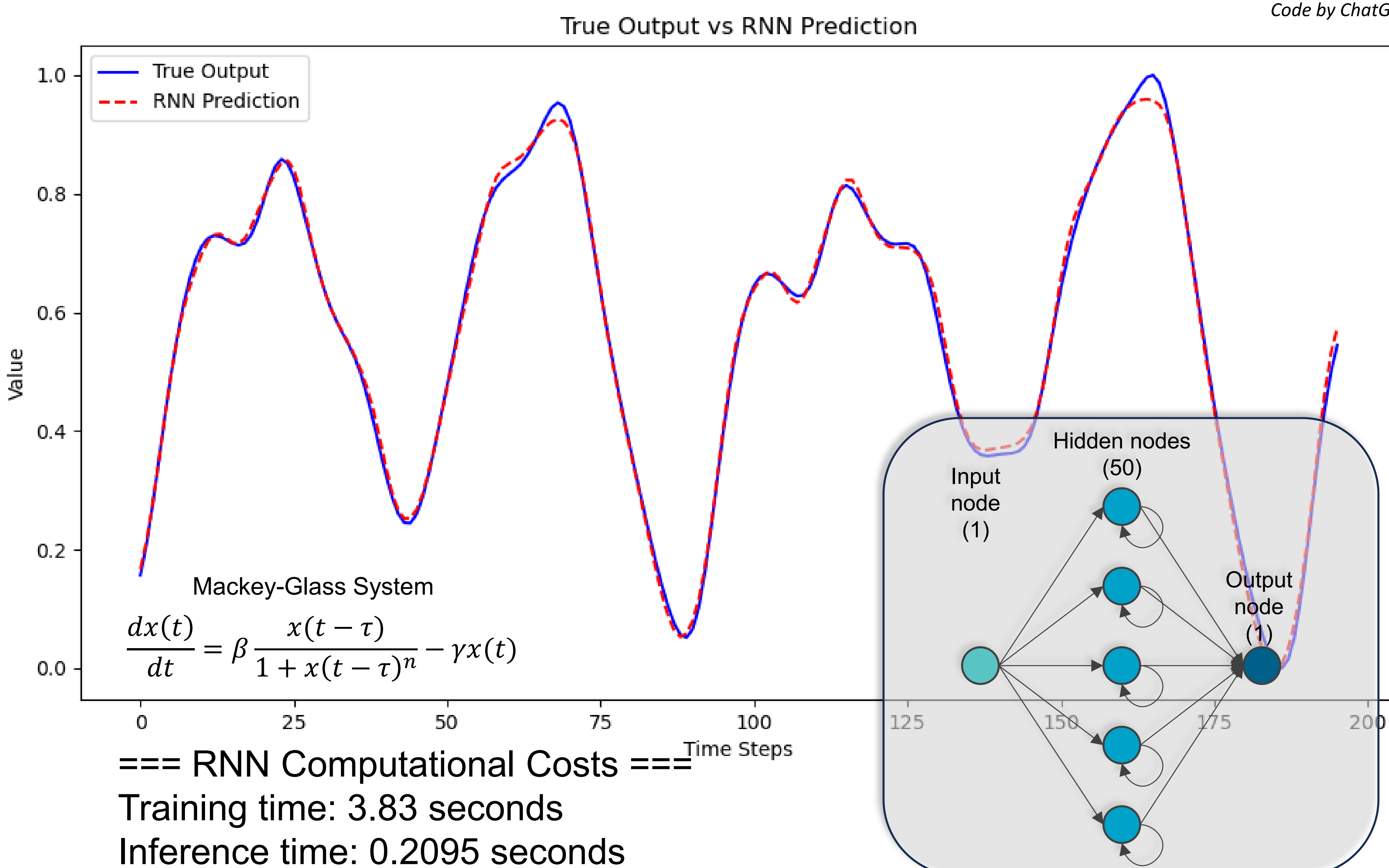


- Reservoir: a set of *randomly created, fixed* recurrent neural network
  - It is passively excited by the input signal and
    maintains nonlinear transformation of the input history in its state.

- The desired output signal is generated
  as *a linear combination of the readout nodes of the reservoir*
  driven by the input signal
  - The linear combination is obtained by linear regression,
    using a teacher signal as a target

UAT for dynamical nonlinear systems

Code by ChatGPT



Mackey-Glass System

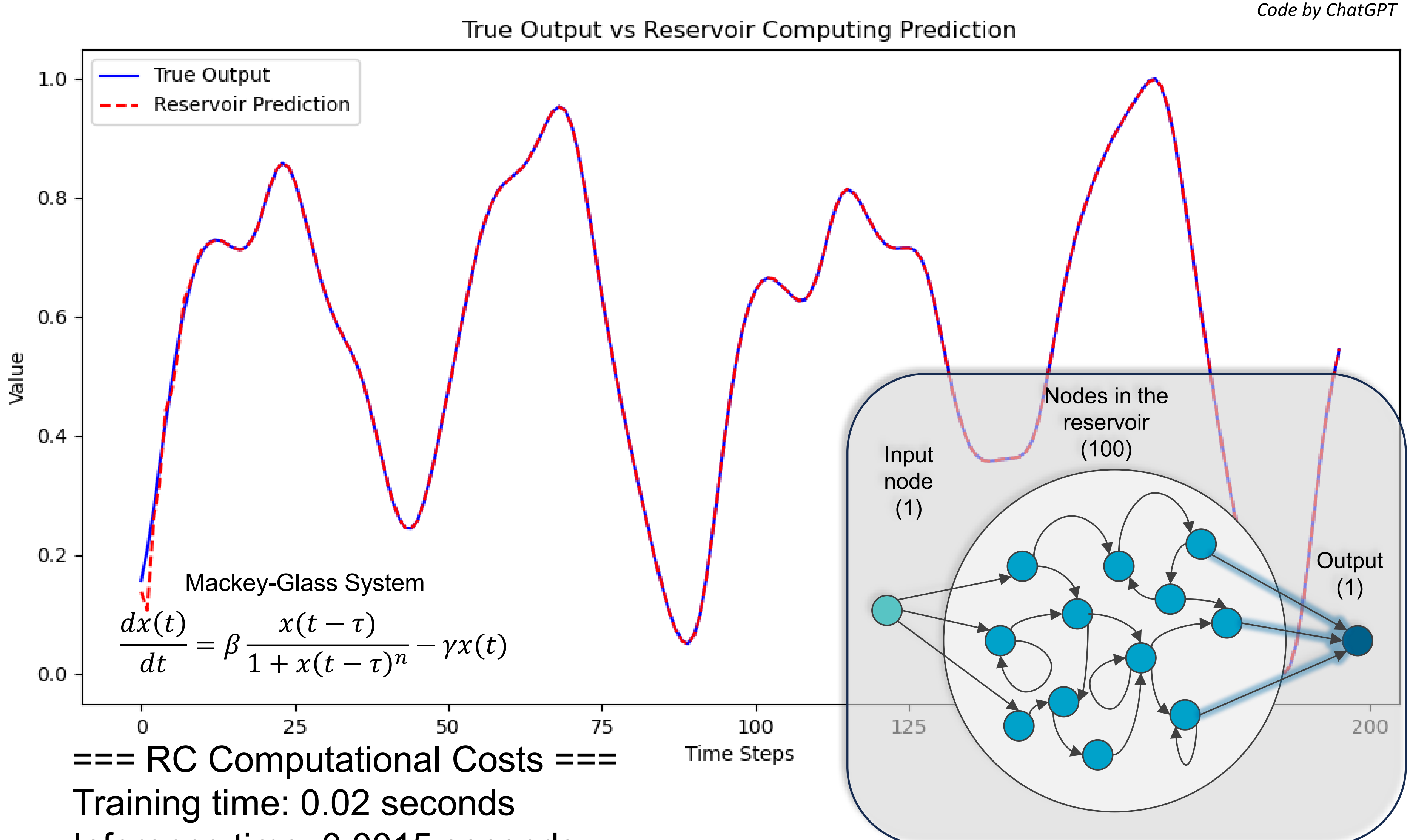
$$\frac{dx(t)}{dt} = \beta \frac{x(t-\tau)}{1 + x(t-\tau)^n} - \gamma x(t)$$

\# of connections to train: 2651

=== RNN Computational Costs ===
Training time: 3.83 seconds
Inference time: 0.2095 seconds
Memory used: 63.27 MB

UAT for dynamical nonlinear systems

Code by ChatGPT



=== RC Computational Costs ===

Training time: 0.02 seconds

Inference time: 0.0015 seconds

Memory used: 5.57 MB

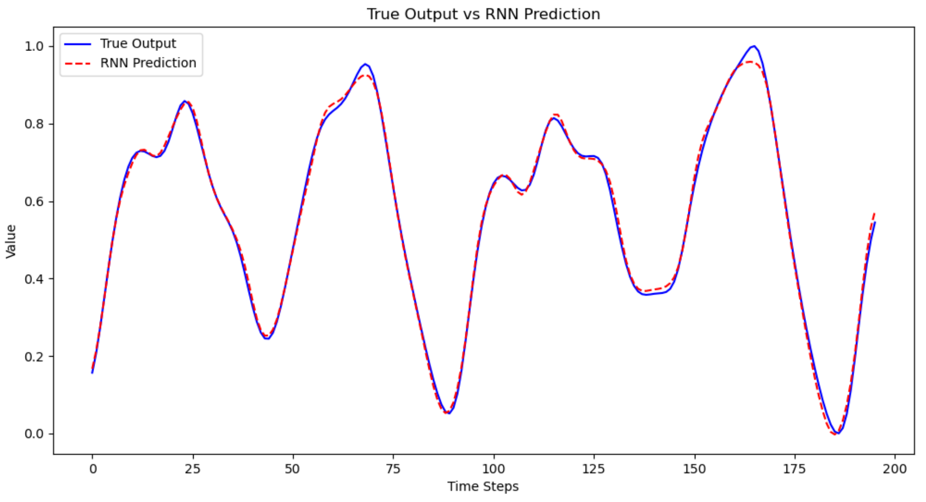
# of readout nodes: 100

# of connections to train: 100

Reservoir computing for cost saving

Code by ChatGPT

Recurrent Neural Network

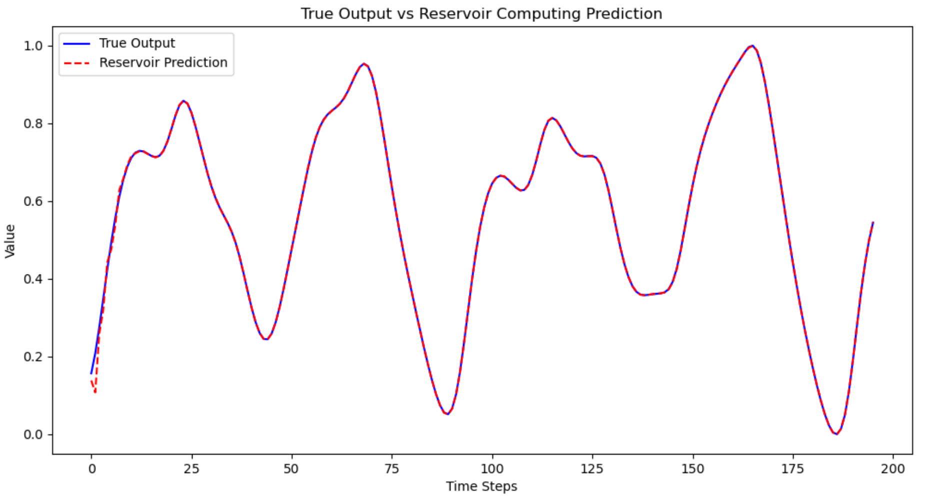


# of Input size: 1 (20 time steps)
# of hidden nodes: 50
# of output node: 1

# of connections to train: 2651

=== RNN Computational Costs ===
Training time: 3.83 seconds
Inference time: 0.2095 seconds
Memory used: 63.27 MB

Reservoir Computing



# of Input size: 1 (20 time steps)
# of nodes in reservoir: 100
# of readout nodes: 100

# of connections to train: 100

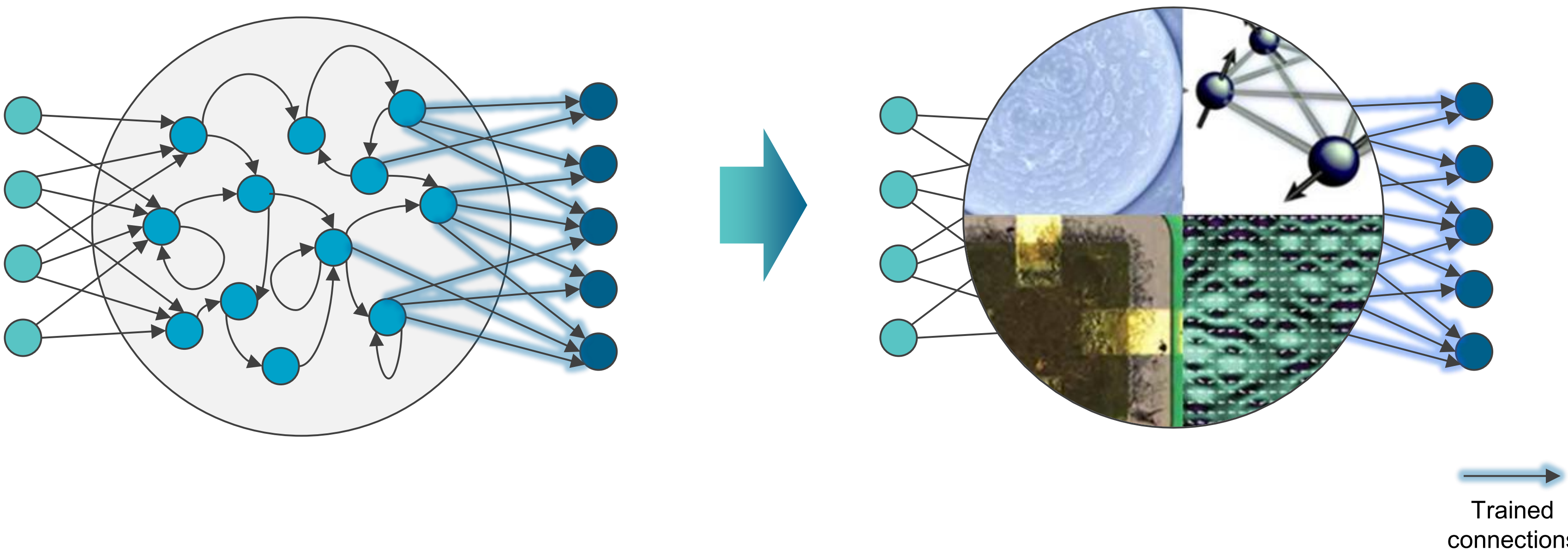
=== RC Computational Costs ===
Training time: 0.02 seconds
Inference time: 0.0015 seconds
Memory used: 5.57 MB

From Reservoir Computing
To Physical Reservoir Computing

‘Physical’ reservoir computing

A reservoir can be a physical system...

Reservoir Computing (RC) **Physical Reservoir Computing (PRC)**



As long as the physical system has the following features:

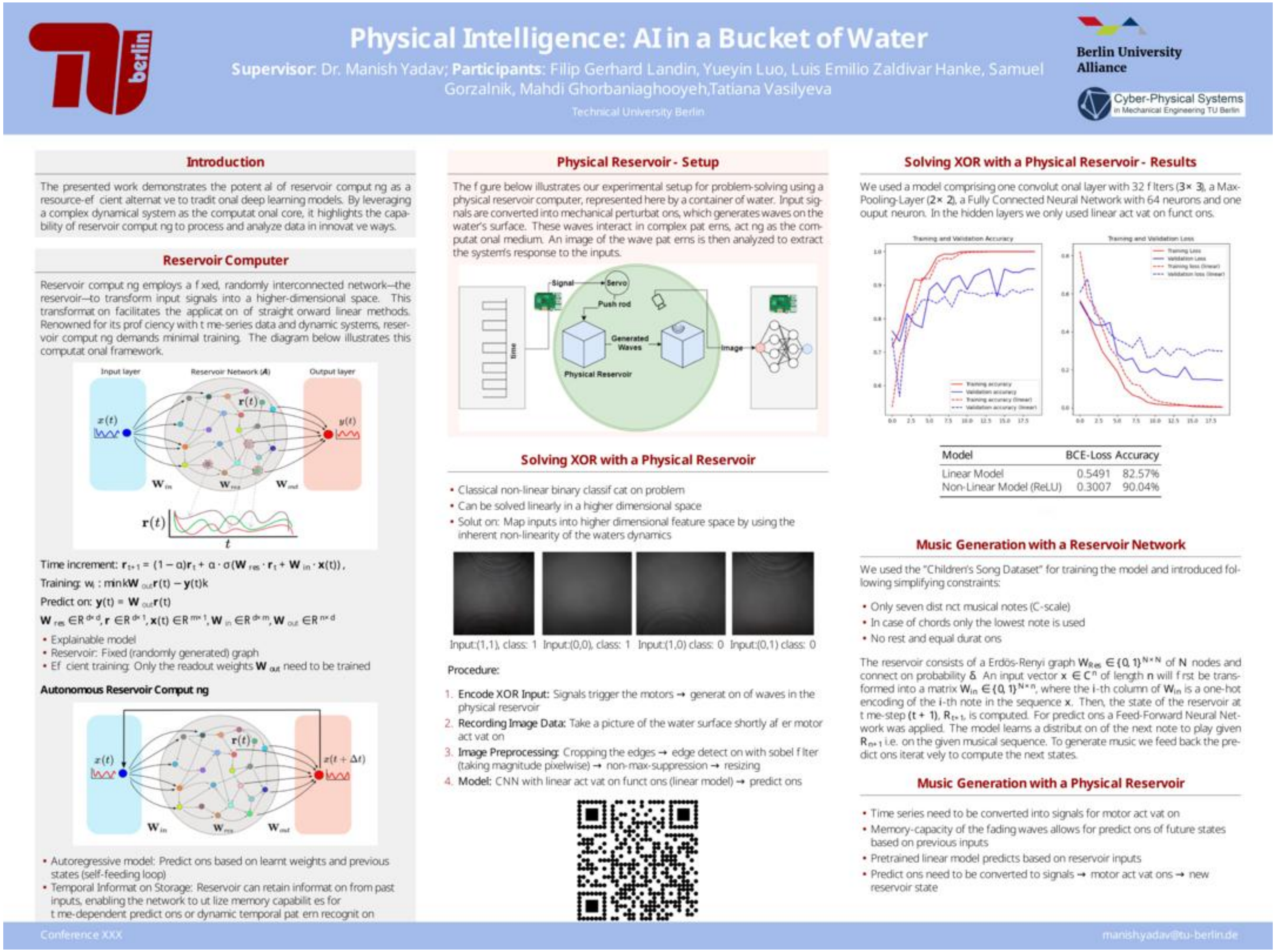
- Have a short-term internal memory – *fading memory*
- Nonlinear transformation of the input data
- Given the same input, same output should be guaranteed

Can water compute?

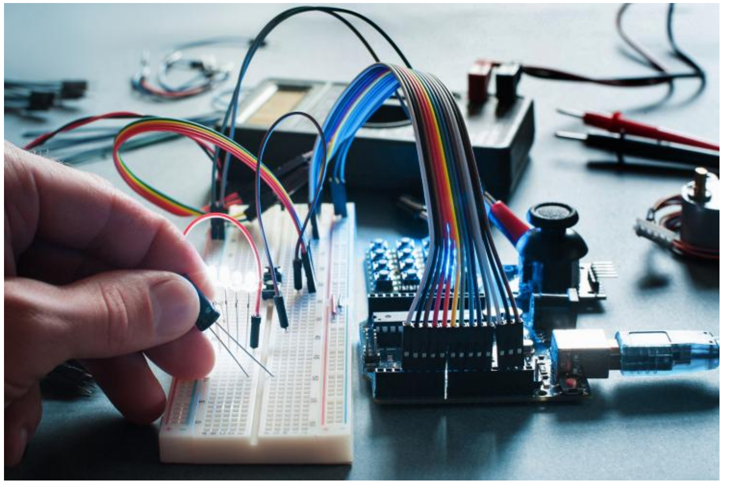
- Same drops: same ripples propagate (Same input – same output)
- Multiple ripples can interfere (Nonlinear transform)
- Ripples will fade away (Fading memory)

Reservoir computing from a water bucket

Source: TU Berlin (Dr. Manish Yadav et al.)



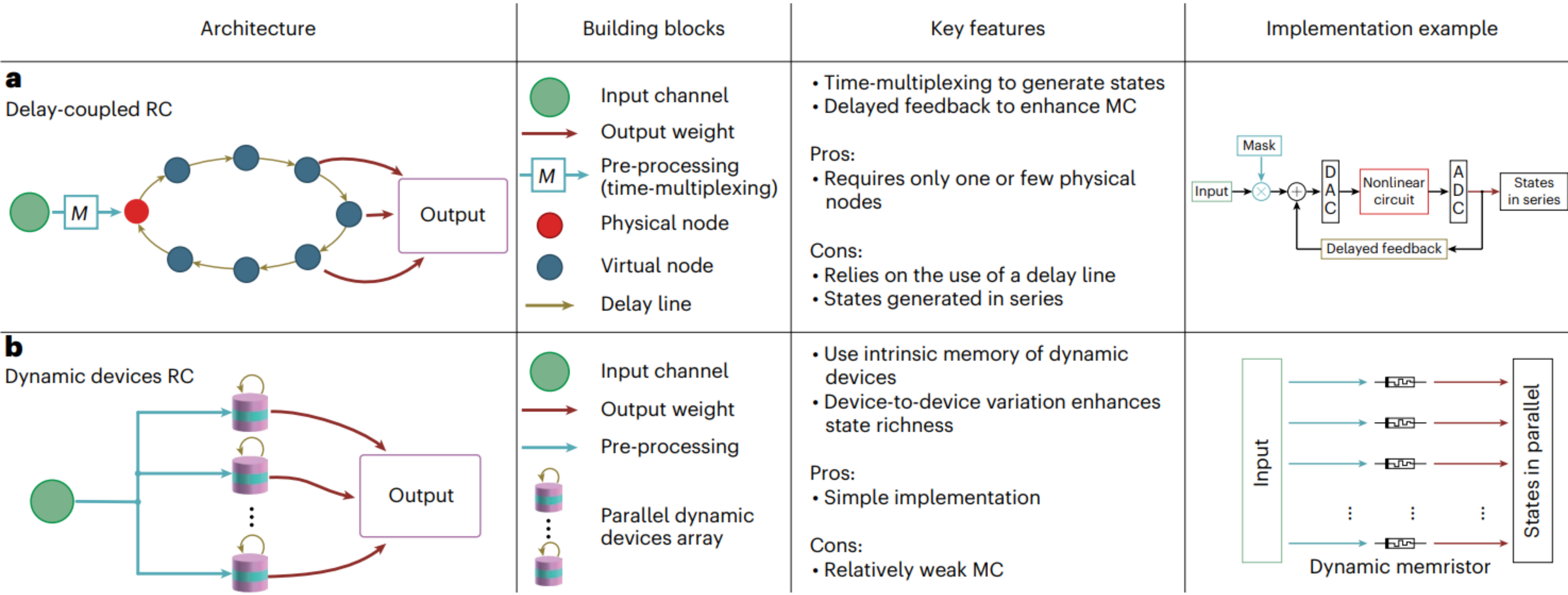
Towards practical applications



- Electronic devices are generally preferred for their versatile applicability
- Making an electronic reservoir requires complicated circuits and connections
- Simple and programmable method to utilize electronic devices as physical reservoir

From Delay-coupled RC to Dynamic devices RC

Ref: X. Liang, J. Tang, Y. Zhong, B. Gao, H. Qian, H. Wu, Physical reservoir computing with emerging electronics. Nature Electronics **7***, 193–206 (2024).*

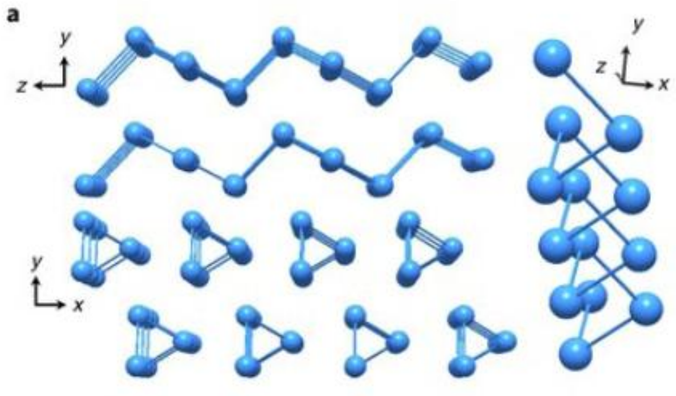


- Delay-coupled RC requires signal masking and delayed feedback in a node, which is usually a circuit module
  - State richness is achieved by *time multiplexing*
- Dynamic devices RC utilizes nonlinearity and fading memory characteristics of a single device and utilize multiple devices in parallel
  - State richness is achieved by *device-to-device variation*

Case study: Physical Reservoir Computing Using Tellurium Photonic Synapses

Reference: Hyerin Jo#, Jiseong Jang#, Hyeon Jung Park#, Huigu Lee, Sung Jin An, Jin Pyo Hong*, Mun Seok Jeong*, and Hongseok Oh*, "Physical reservoir computing using tellurium-based gate-tunable artificial photonic synapses", *ACS Nano*, **18**, 44 (2024): 30761–73.

Te thin film photonic synapse



C. Zhao, C. Tan, D.-H. Lien, X. Song, M. Amani, M. Hettick, H. Y. Y. Nyein, Z. Yuan, L. Li, M. C. Scott, A. Javey, Evaporated tellurium thin films for p-type field-effect transistors and circuits. *Nat. Nanotechnol.* **15**, 53–58 (2020).

Collaboration with:

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Prof. Jin-Pyo Hong (Hanyang Univ.)

Co-first authors:
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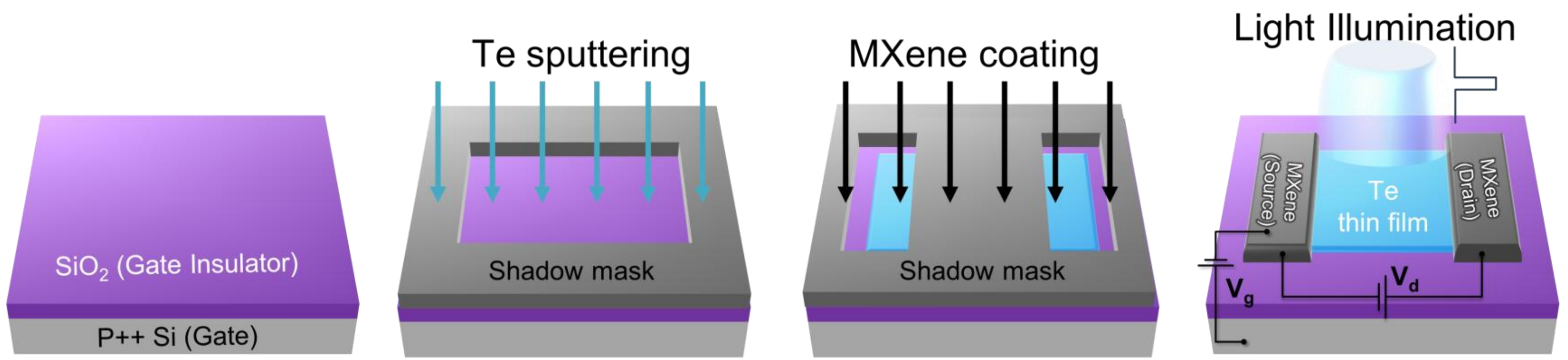
Mr. Jiseong Jang
Dr. Hyeon Jung Park

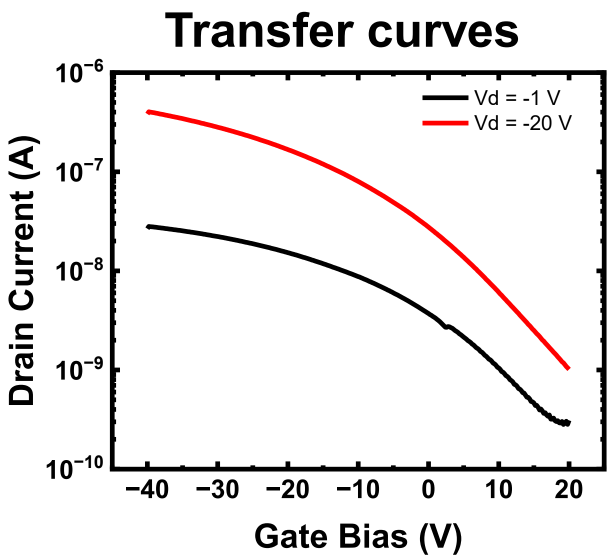
- Te thin film is now receiving a lot of interest as a candidate for high performance p-type materials
- Potential for synaptic CMOS system
- Multi-colored light applications (Small bandgap)

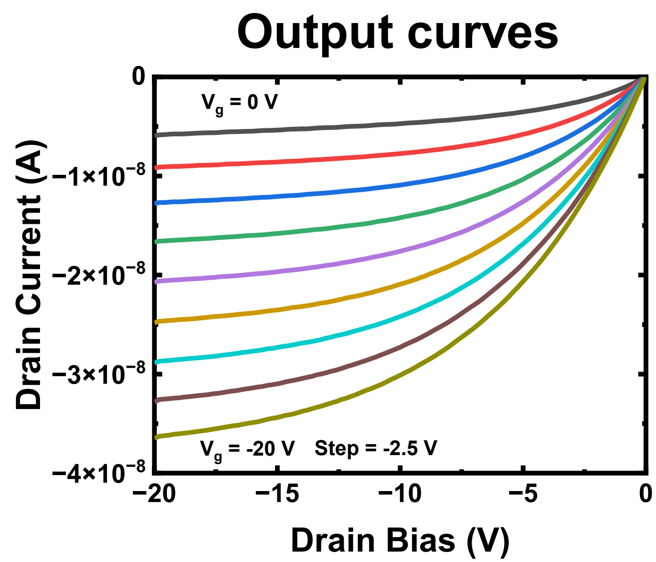
Te thin film photonic synapse

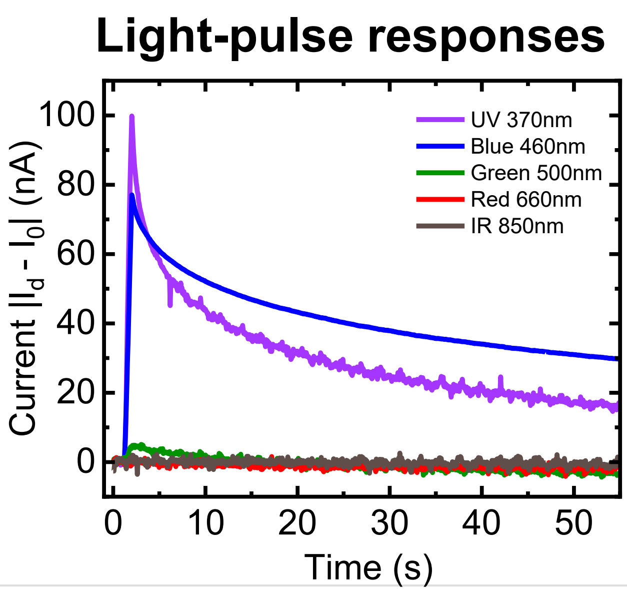


- Te thin film device with back-gate structure

Te TFT as p-type TFT

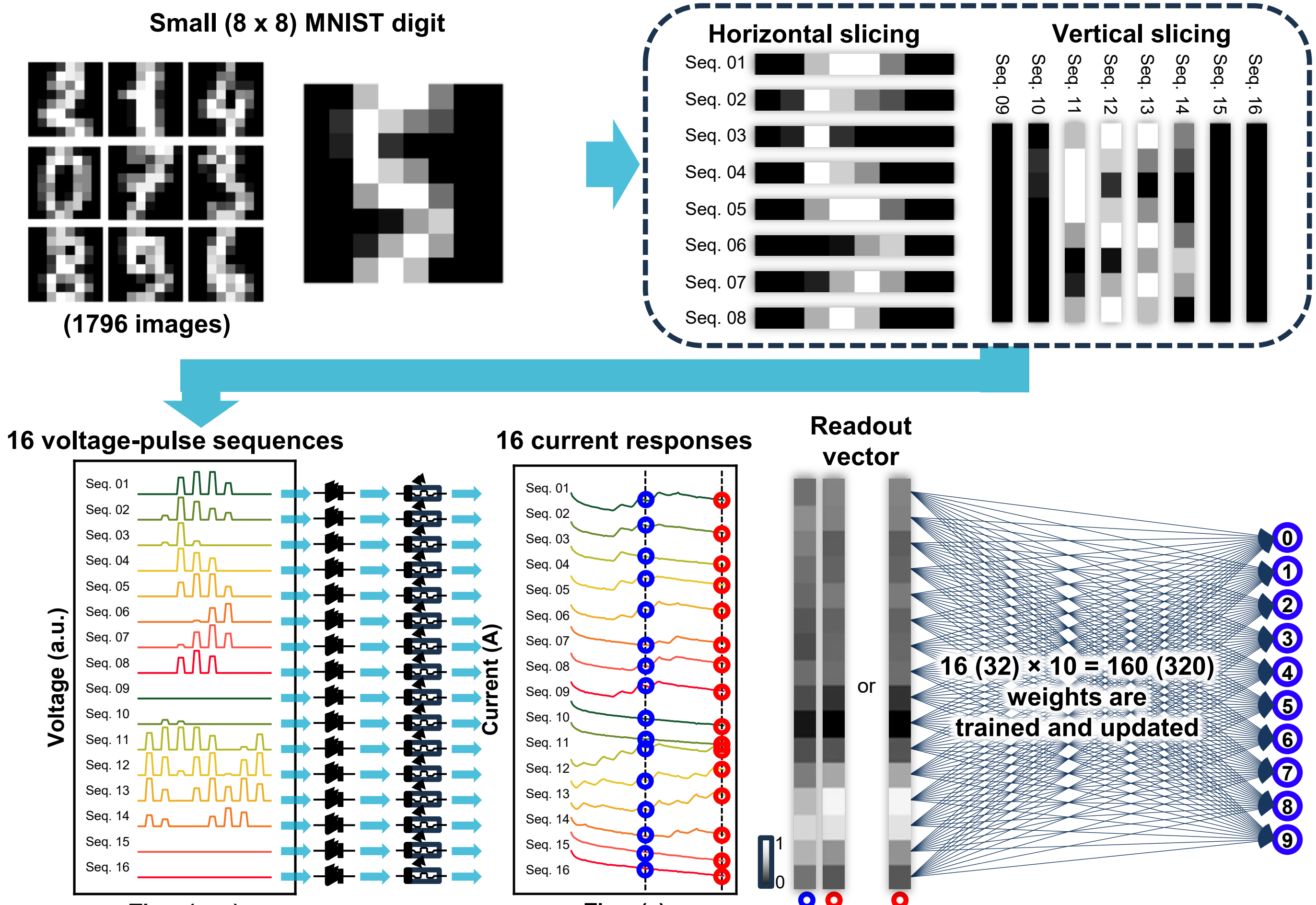






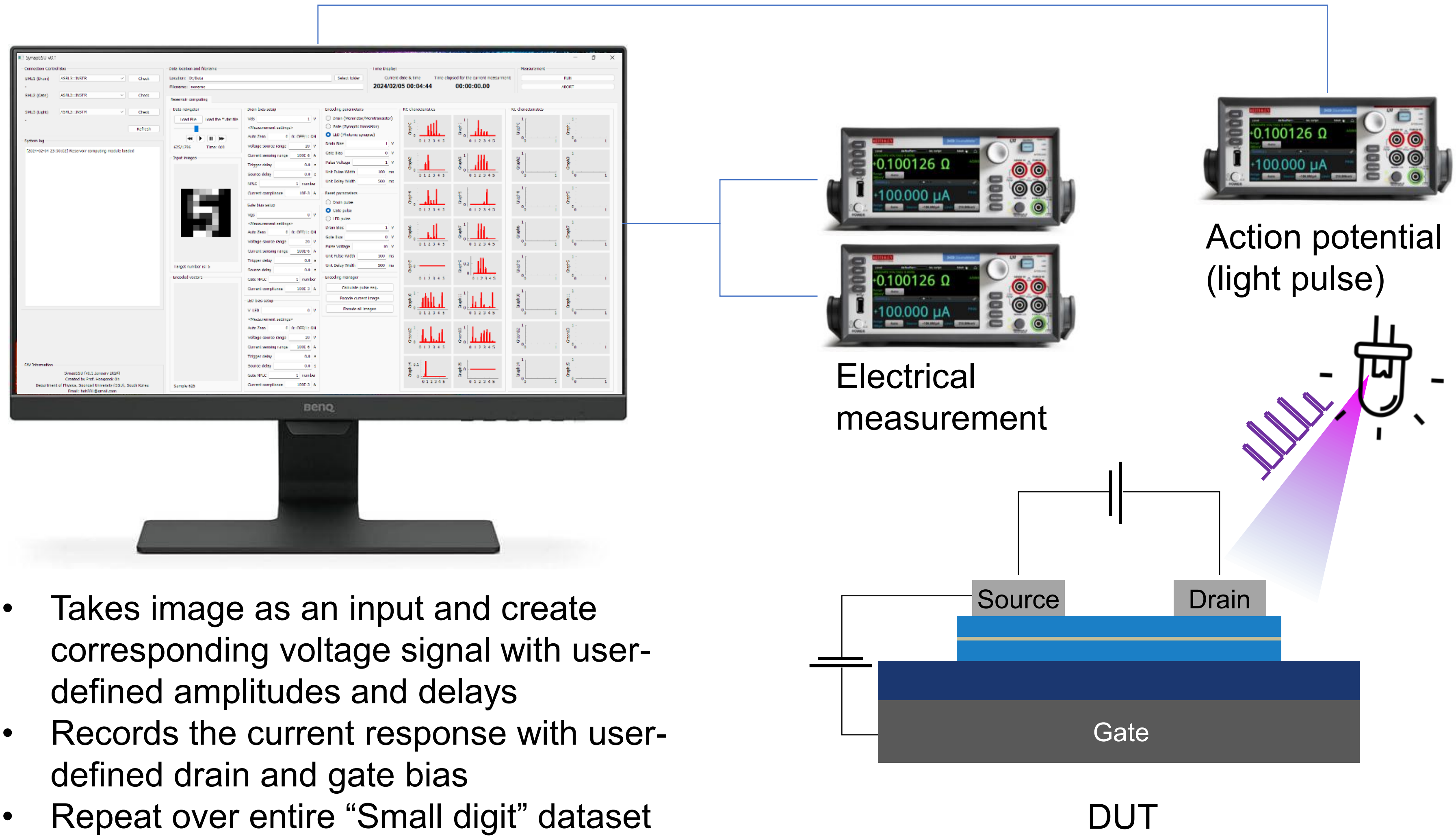
- Te thin film transistor is a p-type transistor
- Strong response to UV and blue lights

Small MNIST classification task



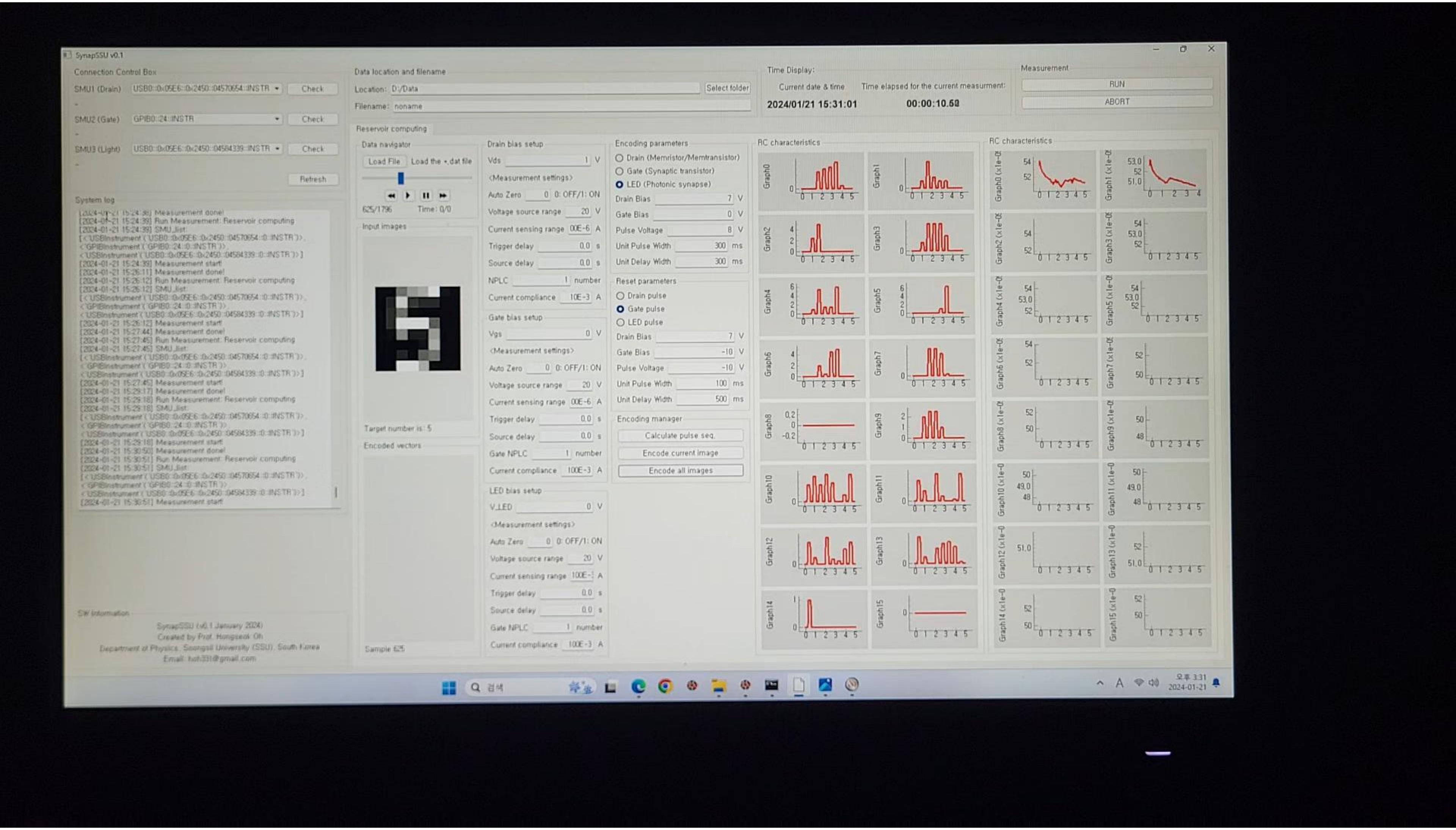
- No binarization: Used value as a LED intensity
- Final conductance values were used for learning
- # of connections for training: 64 (No RC) -> 16 (RC)
- In principle parallel computation is possible

System Implementation



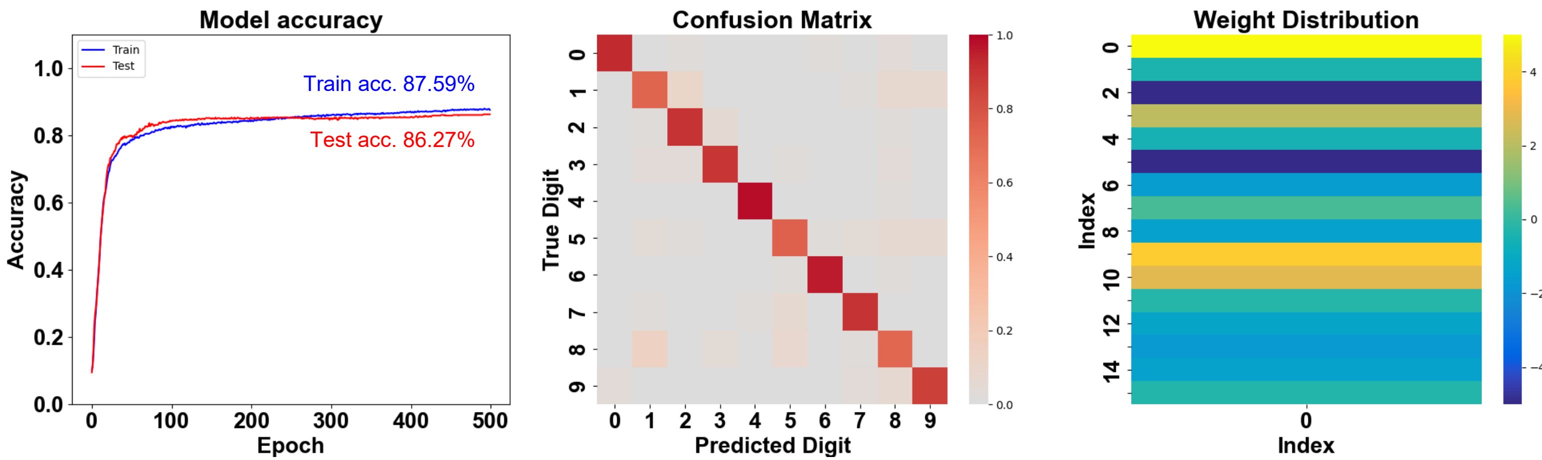
- Takes image as an input and create corresponding voltage signal with user-defined amplitudes and delays
- Records the current response with user-defined drain and gate bias
- Repeat over entire “Small digit” dataset (1697 images from Scikit Learn)

System Implementation

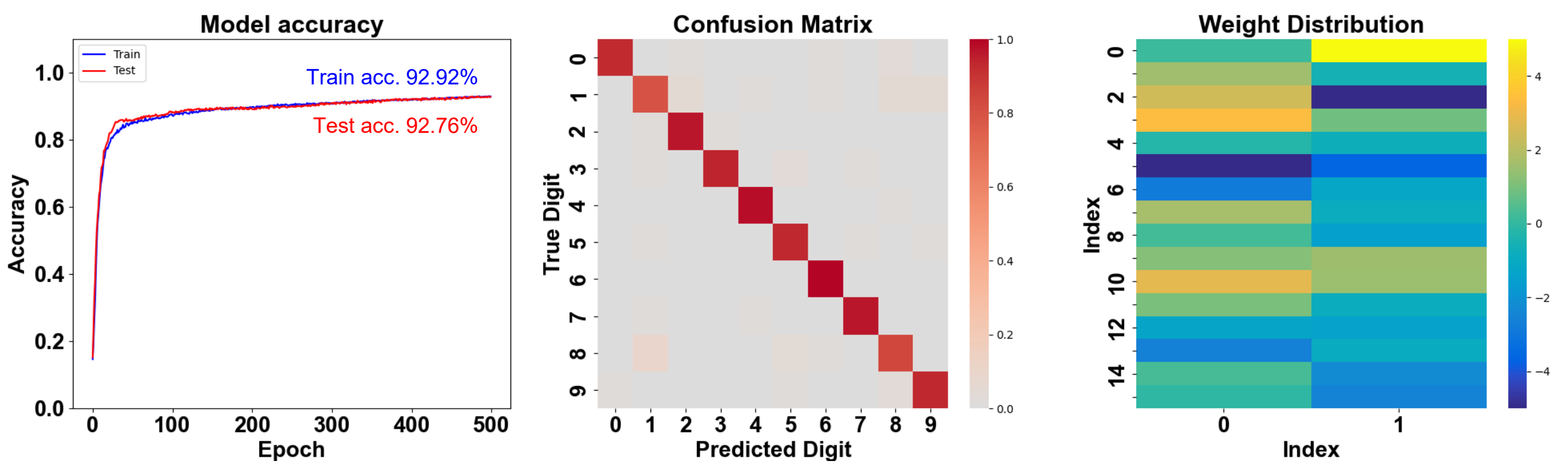


Results

16-valued readout

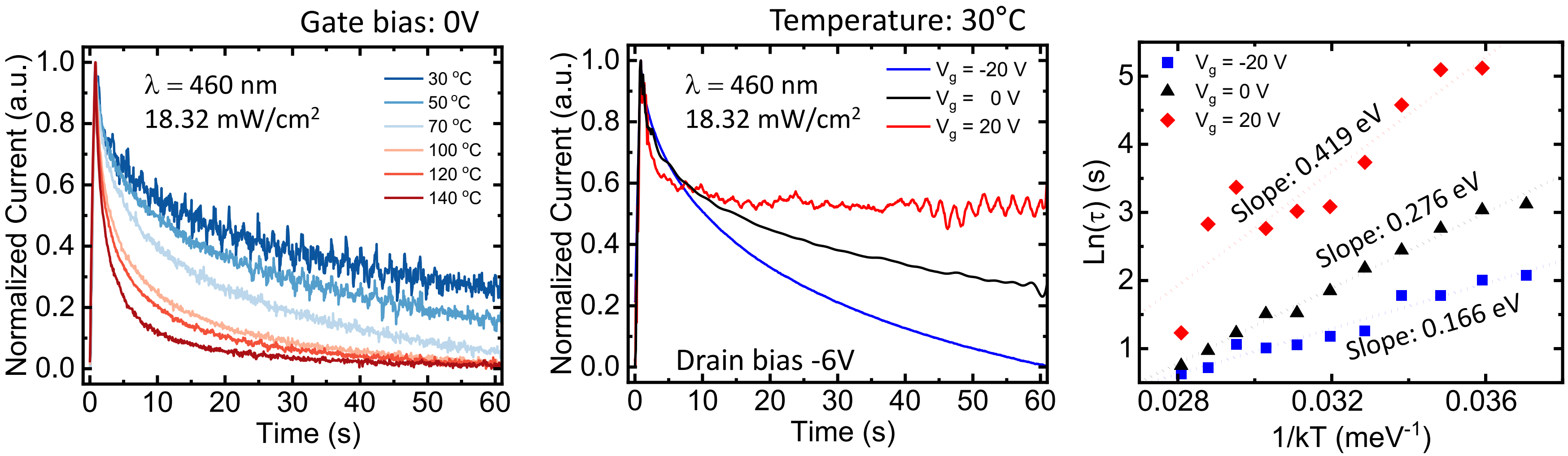


32-valued readout



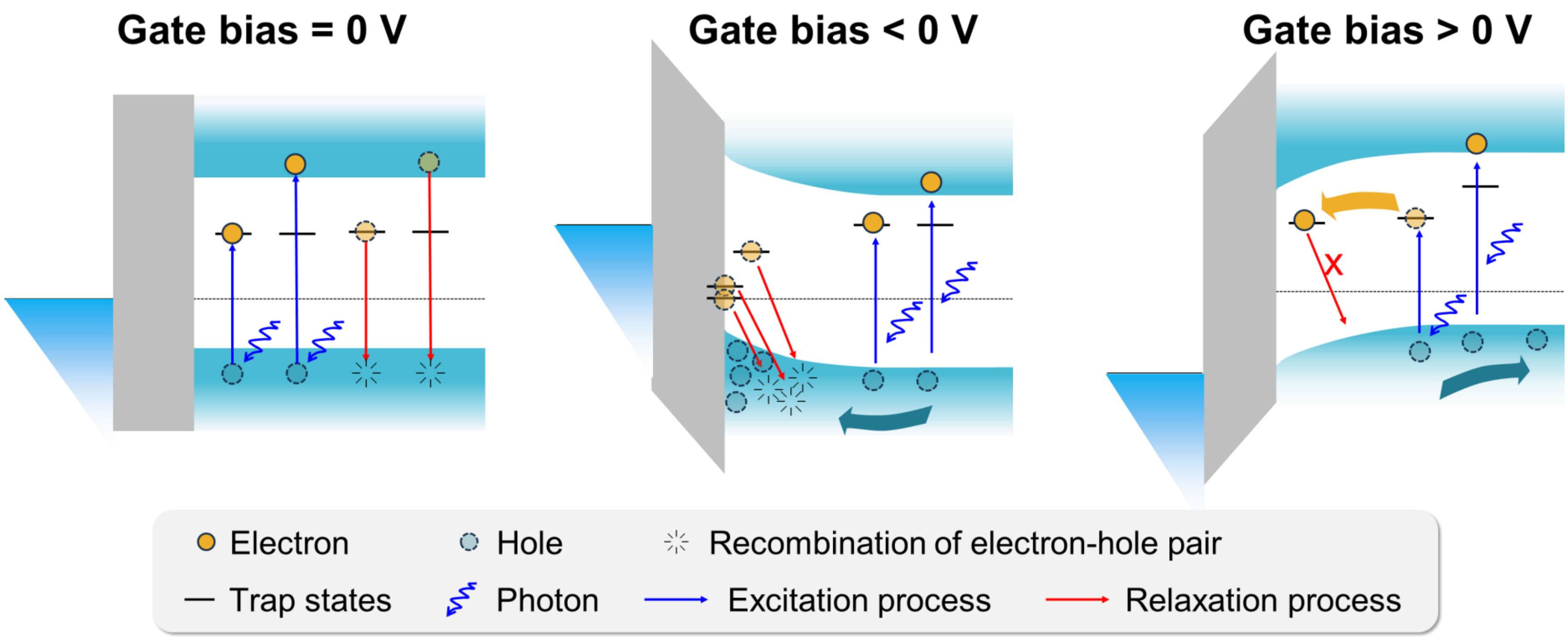
- Sample #: 1796, 70% for training, 30% for validation

Temperature dependent PPC



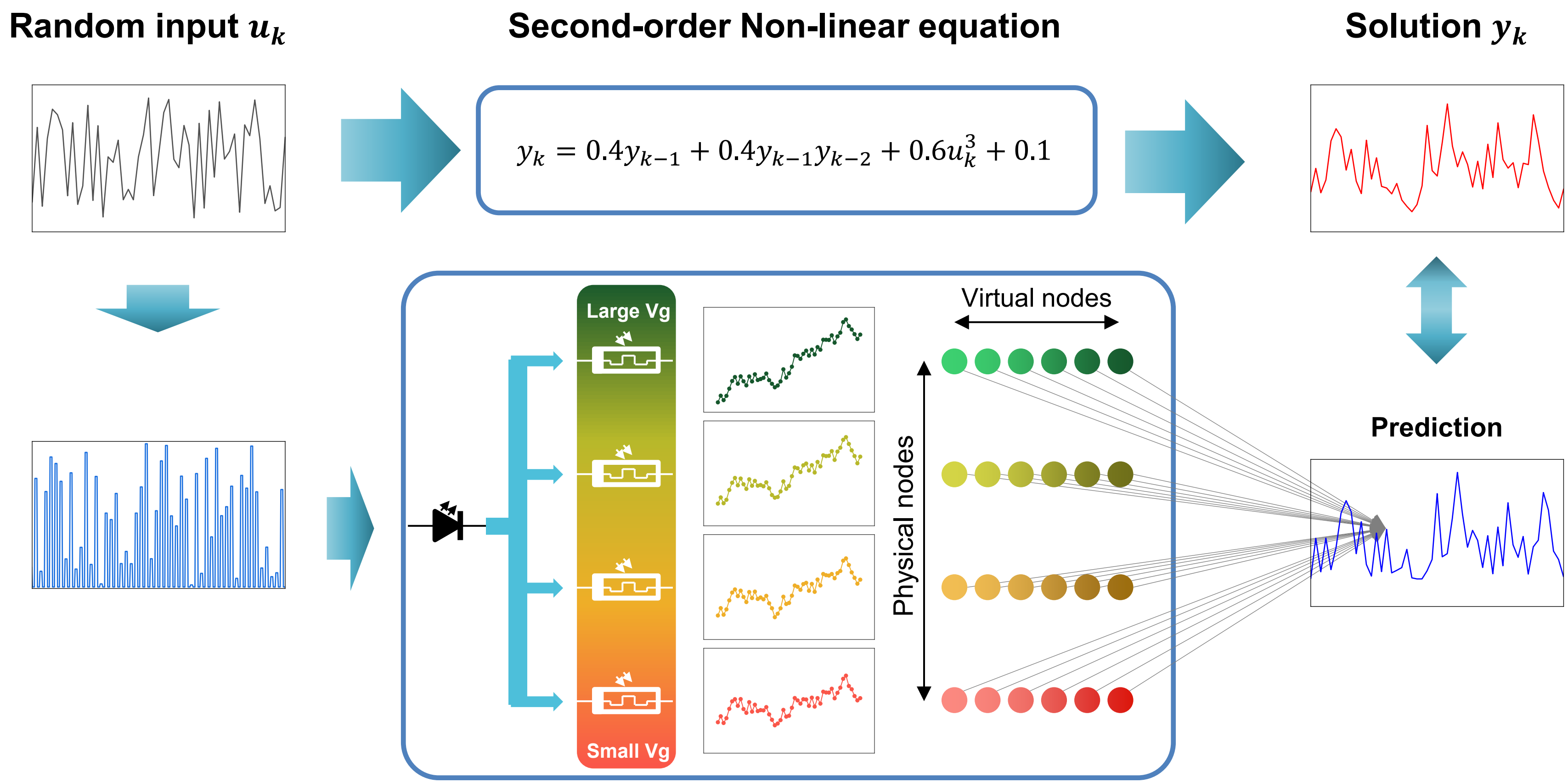
- Temperature dependent PPC with decreasing time constant at elaborated temperature
- The time constant can be tuned by the gate bias
- The energy related to trapping of photo-generated carriers are expected to be 166 – 419 eV depending on the gate bias

Temperature dependent PPC



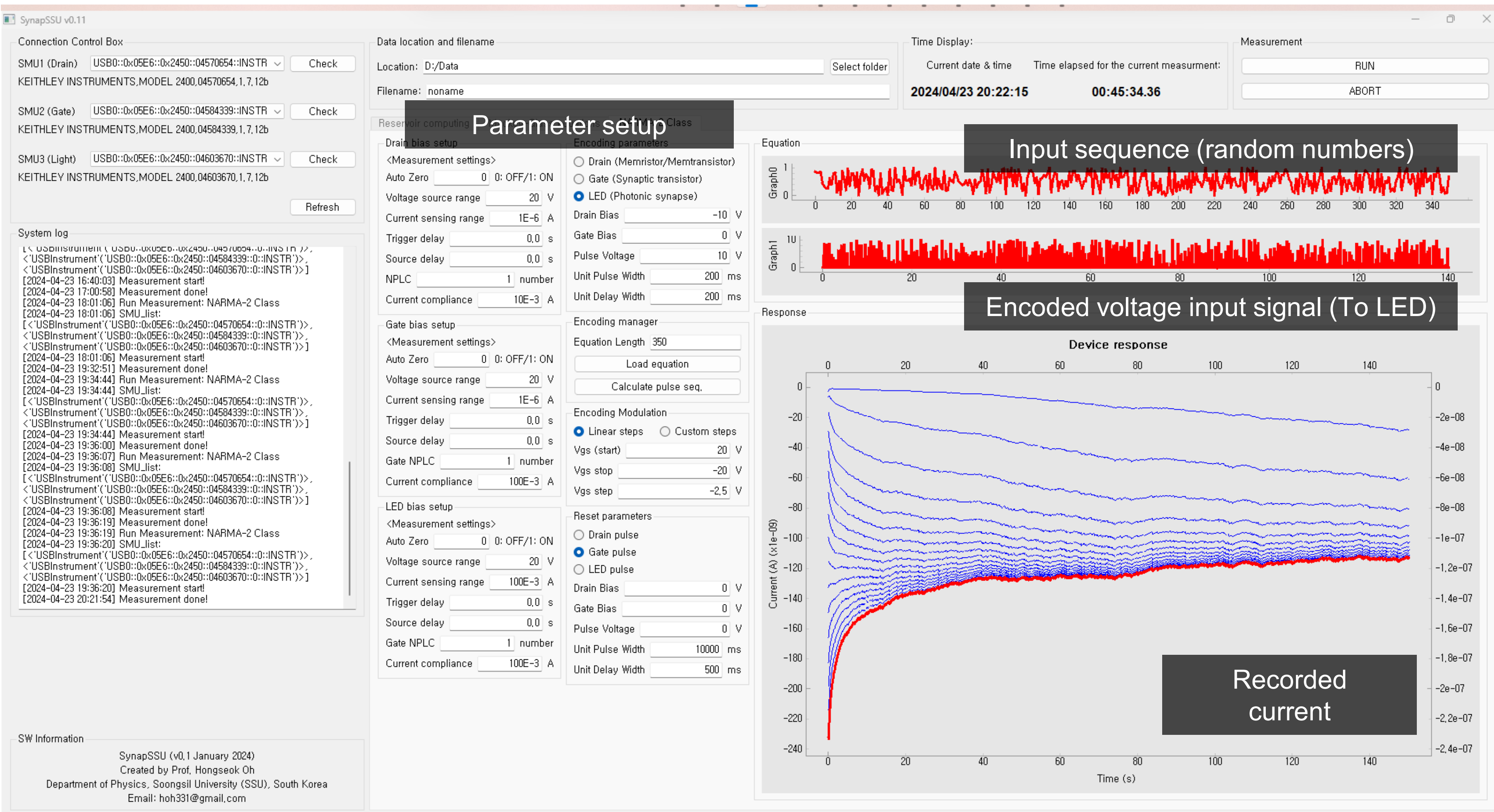
- Negative bias attracts holes to the front channel.
  They recombine with electrons in the trap sites.
- Positive bias pushes holes to the back channel, while the electrons are attracted to the front channel, leading to the prolonged recombination.

Prediction of the Solution for Non-Linear Equation



- Reservoir computing can be used to predict the solution of non-linear equation

Prediction of the Solution for Non-Linear Equation



Prediction of the Solution for Non-Linear Equation

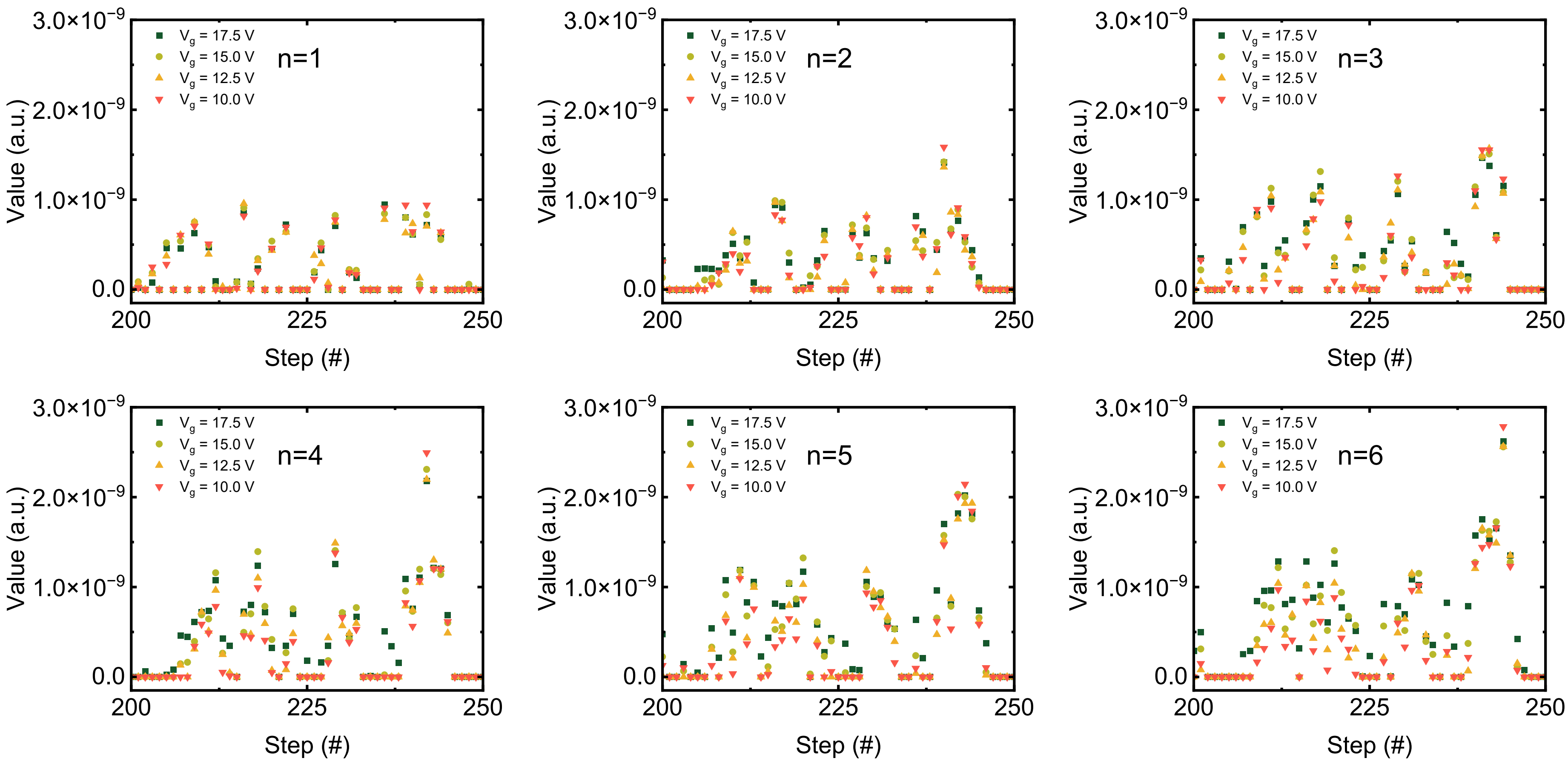
$$x_k^i = I_k^i - I_{k-n}^i \qquad \text{if } I_k^i - I_{k-n}^i > 0$$

$$x_k^i = 0 \qquad \text{if } I_k^i - I_{k-n}^i \leq 0$$

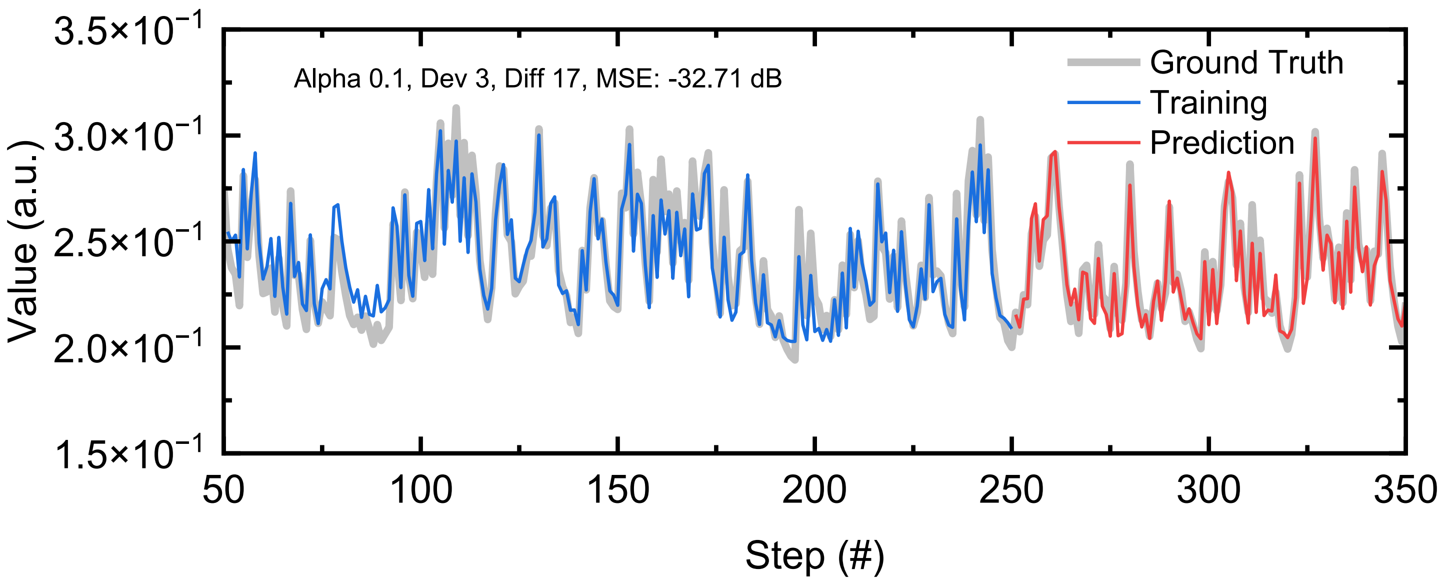
k : step #

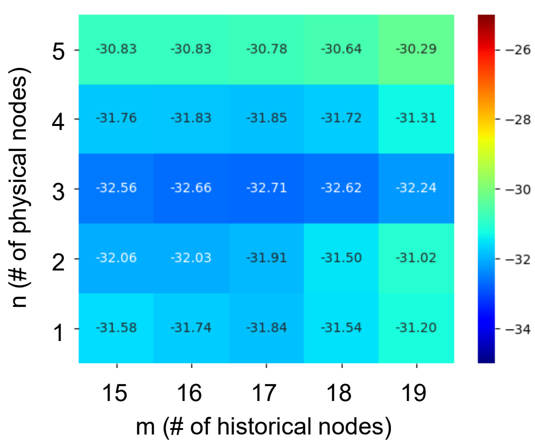
i : device index

n : differential index



Prediction of the Solution for Non-Linear Equation

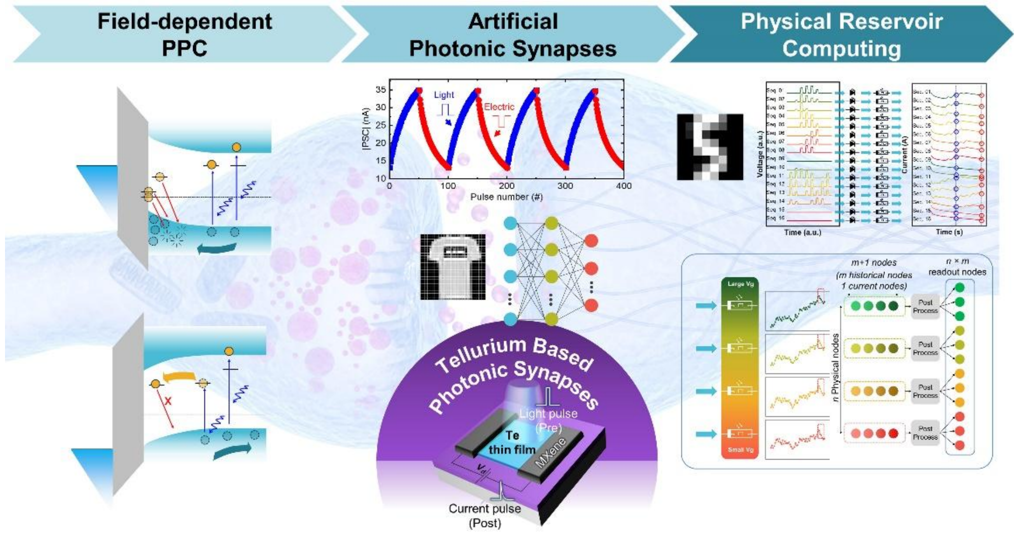




$$\text{NMSE} = \frac{1}{T}\frac{\sum_{k=1}^{T}[y_t(k) - y(k)]^2}{\sum_{k=1}^{T}[y_t(k) - y_{\text{ave}}]^2}$$

- Accurate prediction of the solution is possible from this PRC approach

Conclusion



- Reservoir computing is a new energy-saving framework for learning nonlinear dynamical systems

- Physical reservoir computing replaces the software reservoir with a physical one to achieve maximized cost saving

- Dynamic devices can be used as a physical reservoir – a new way to implement physical reservoir computing with existing electronics

Acknowledgement


March 2024 Group dinner

Group members

Professor:

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Prof. Jaegoo Lee

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Prof. Jin Pyo Hong (Hanyang Univ.)

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