Neurons in our Brains vs ANN

How different are they?

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Danfoss

UNIVERSITY OF BATH

neuro space

UCRC

xtel

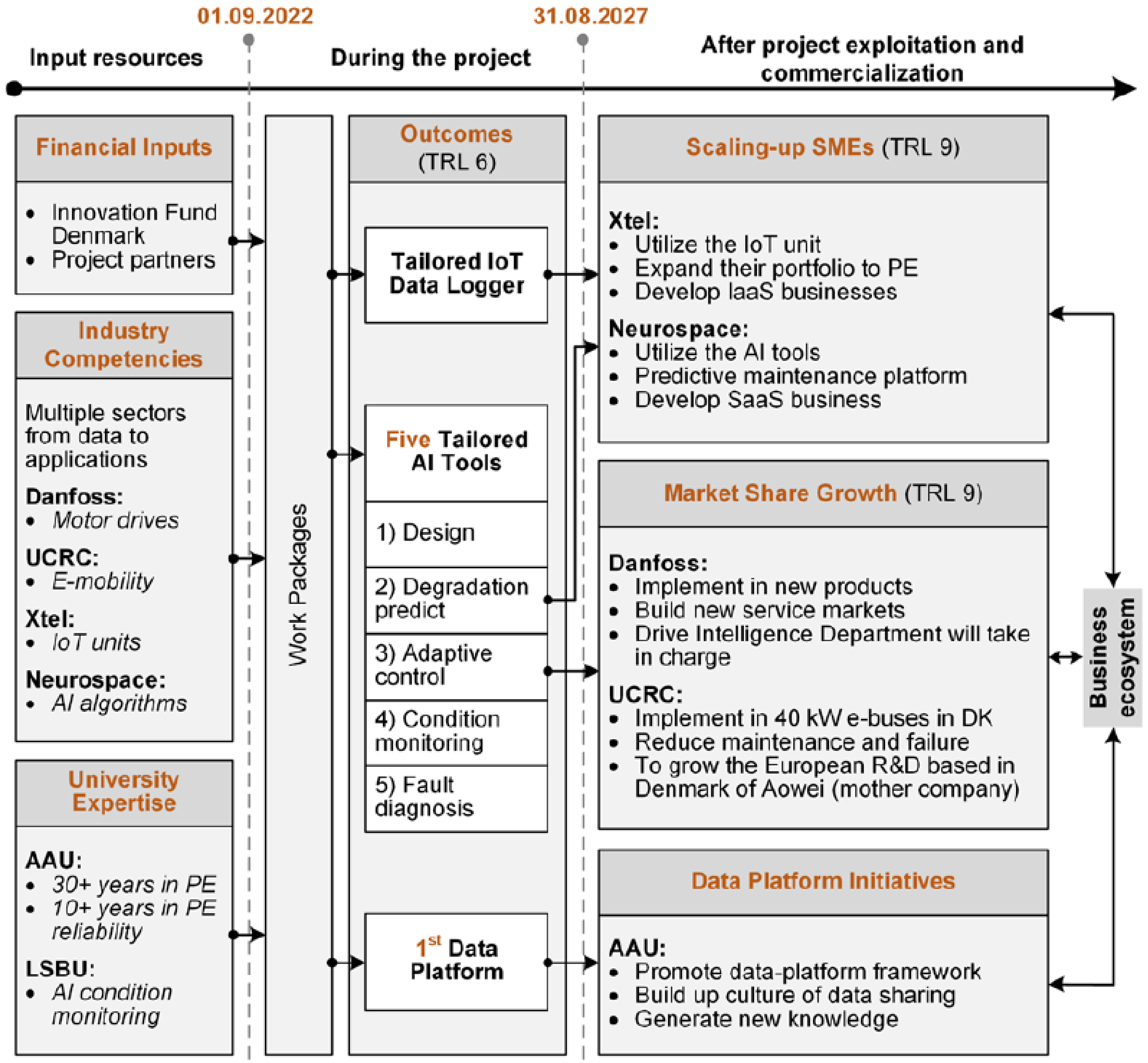
01: 5 tailored AI tools

- Design optimization
- Degradation prediction
- Adaptive control
- Condition monitoring
- Fault prediction and diagnosis

02: 1/3 Reduction

- Design optimization time
- Operating energy loss
- Maintenance cost

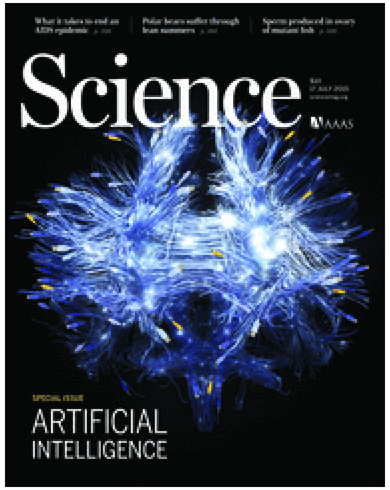
03: The world's 1st power electronics data platform

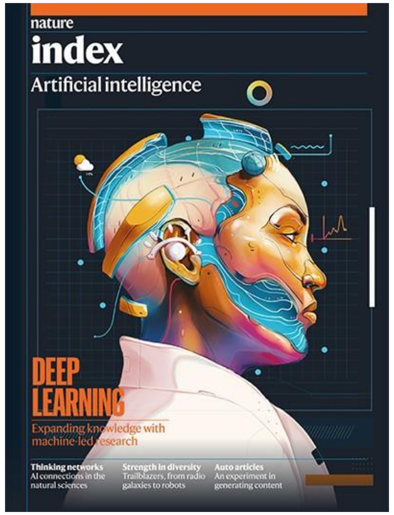


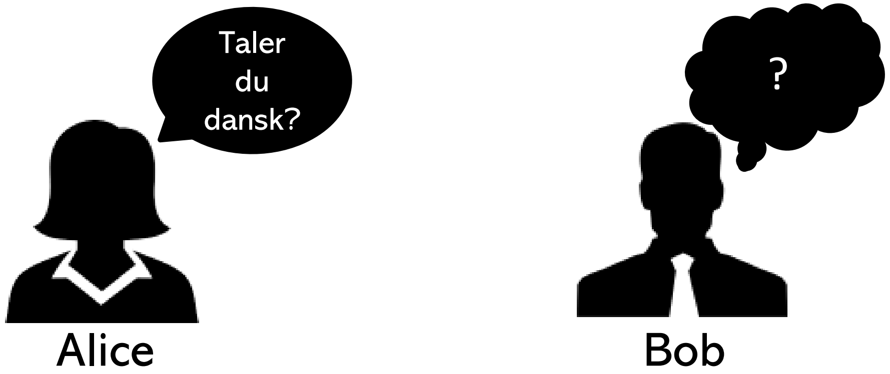
Innovation Fund Denmark

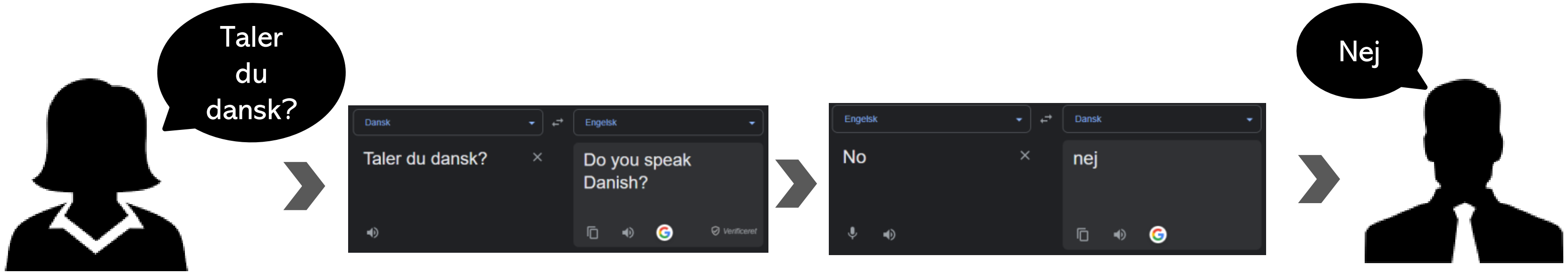
More updates: https://www.ipower.ai/

▶ Machine Learning Today





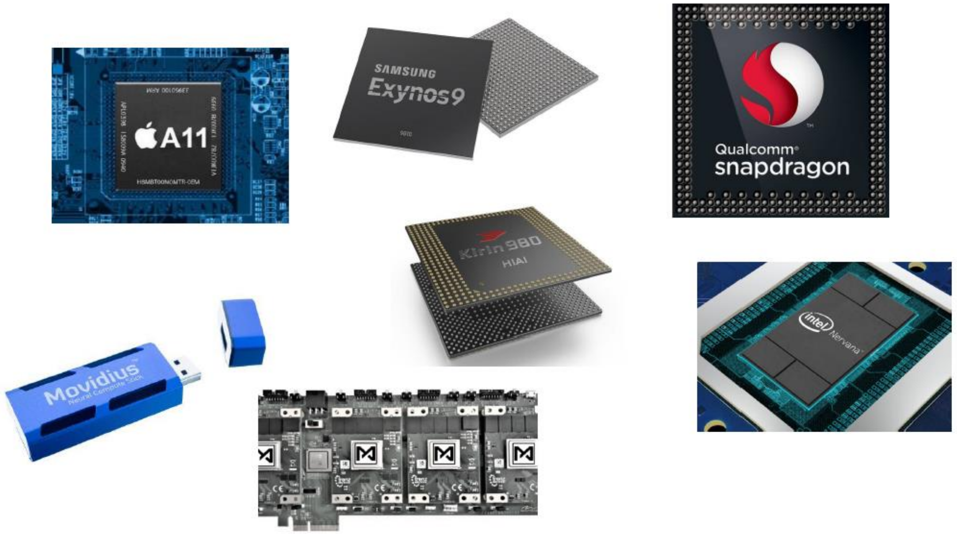


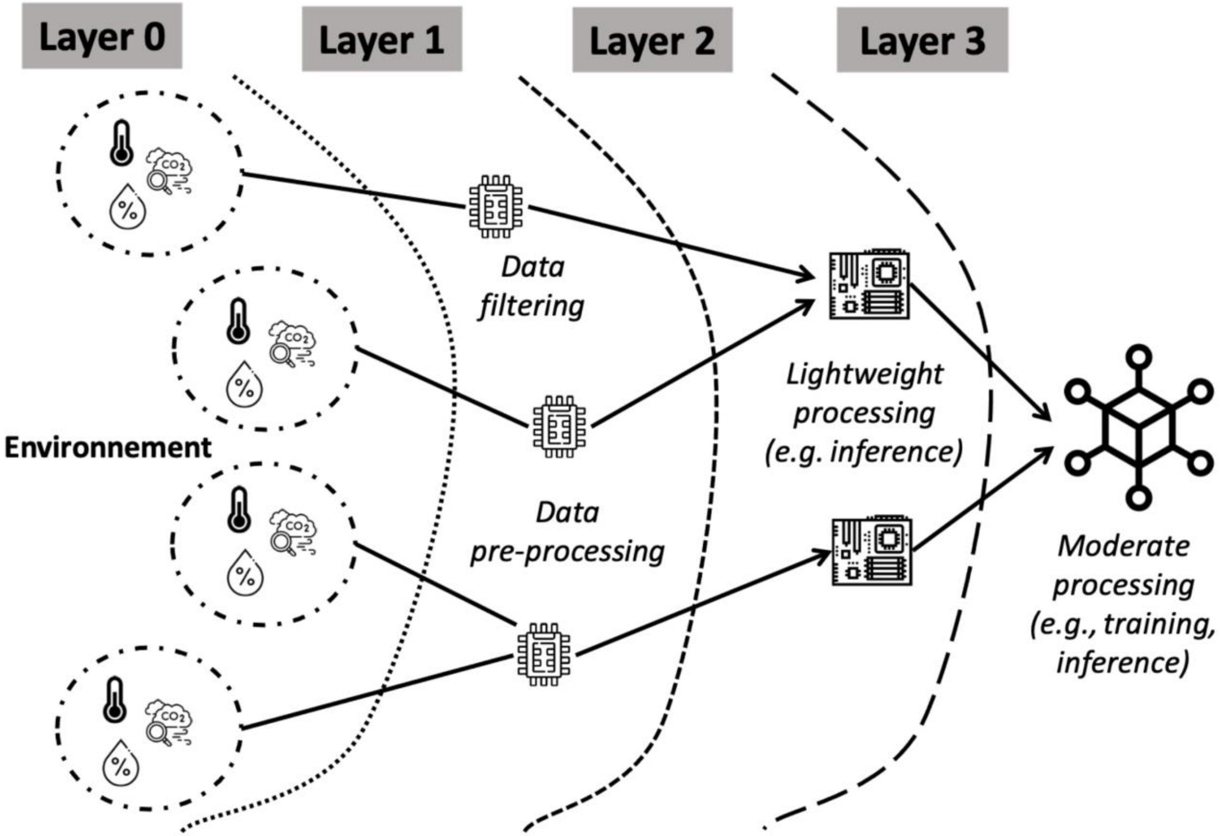


Breakthroughs in ML using (deep) Articial Neural Networks (ANNs) have come at the expense of massive memory, energy, and time requirements

▶ Machine Learning at Edge

- A solution is mobile edge or cloud computing: offline load computations to an edge or cloud server
- Another solution is to scale down energy and memory requirements of ANNs via tailored hardware implementations for mobile devices
    - Active field with established players and start-ups
    - Trade-offs between accuracy and complexity
    - Mostly limited to inference





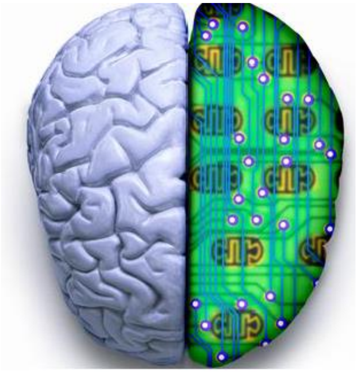
The conventional inference cycle

Source: Lucas Wisnieweski, “Hardware Solutions for Low-Power Smart Edge Computing, “Journ. Low Power Electron. Appl., 2022

► Beyond ANN

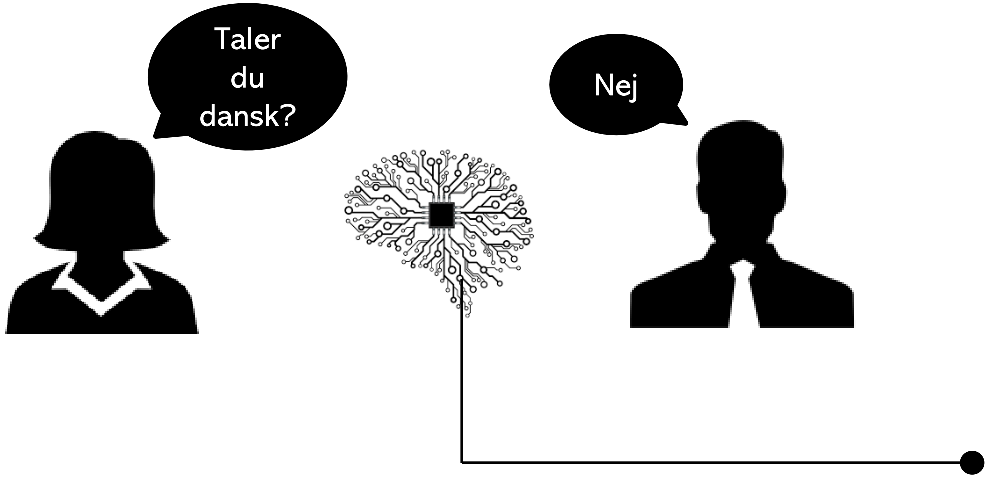
13 Million Watts
5600 sq. ft. & 340 tons
10^{10} ops/J

20 Watts
2 sq. ft. & 1.4 Kg
10^{15} ops/J



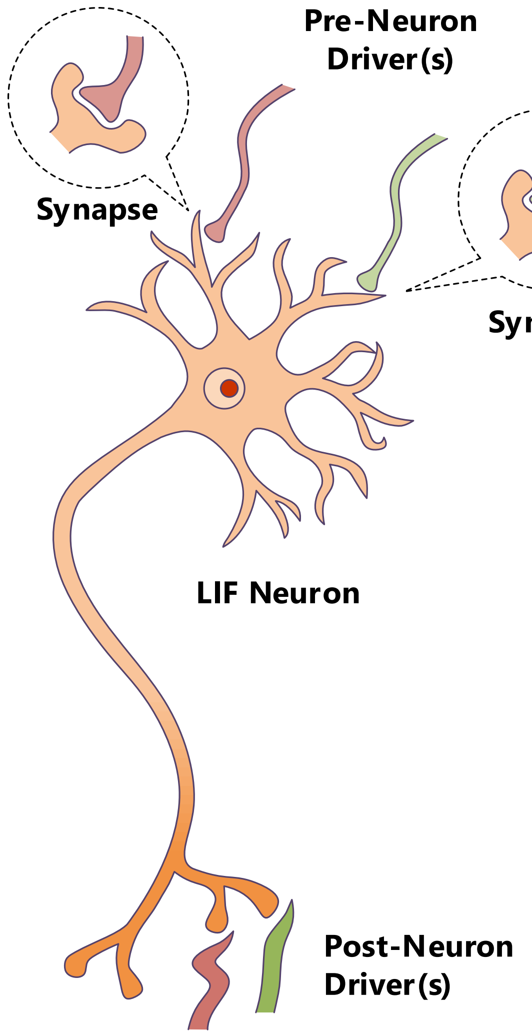
Source: https://www.olcf.ornl.gov, Google Images

A sustainable fast-track process

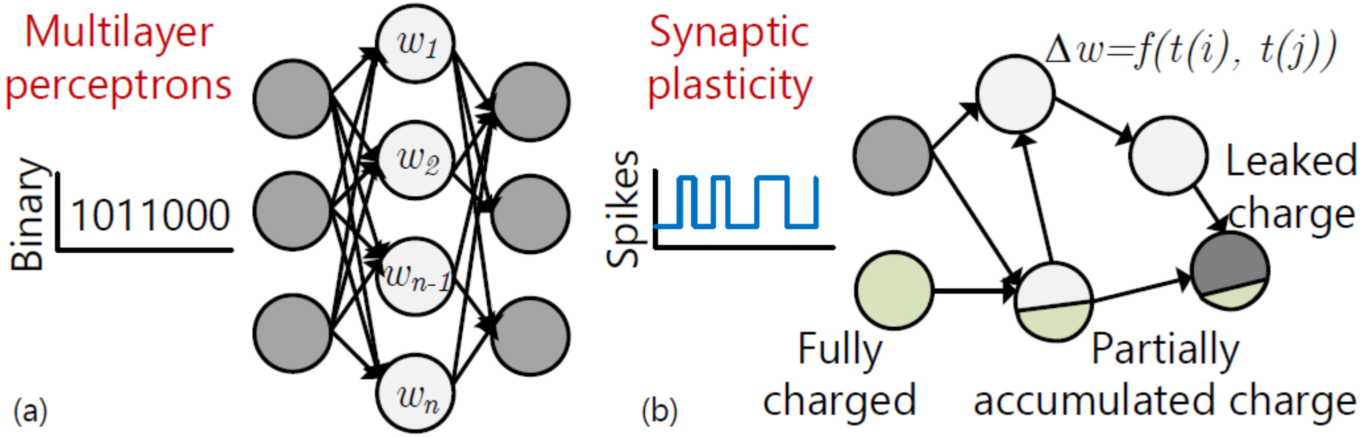


- Energy-efficient
- Sparse and dynamic
- Event-driven learning and inferences
- Online actions

▶ Actually..



- Neurons in the brain sense, process, and communicate over time using sparse binary signals (spikes or action potentials).
- This results in a dynamic, sparse, and event-driven learning and inference.
- Spiking signals minimize energy per bit.

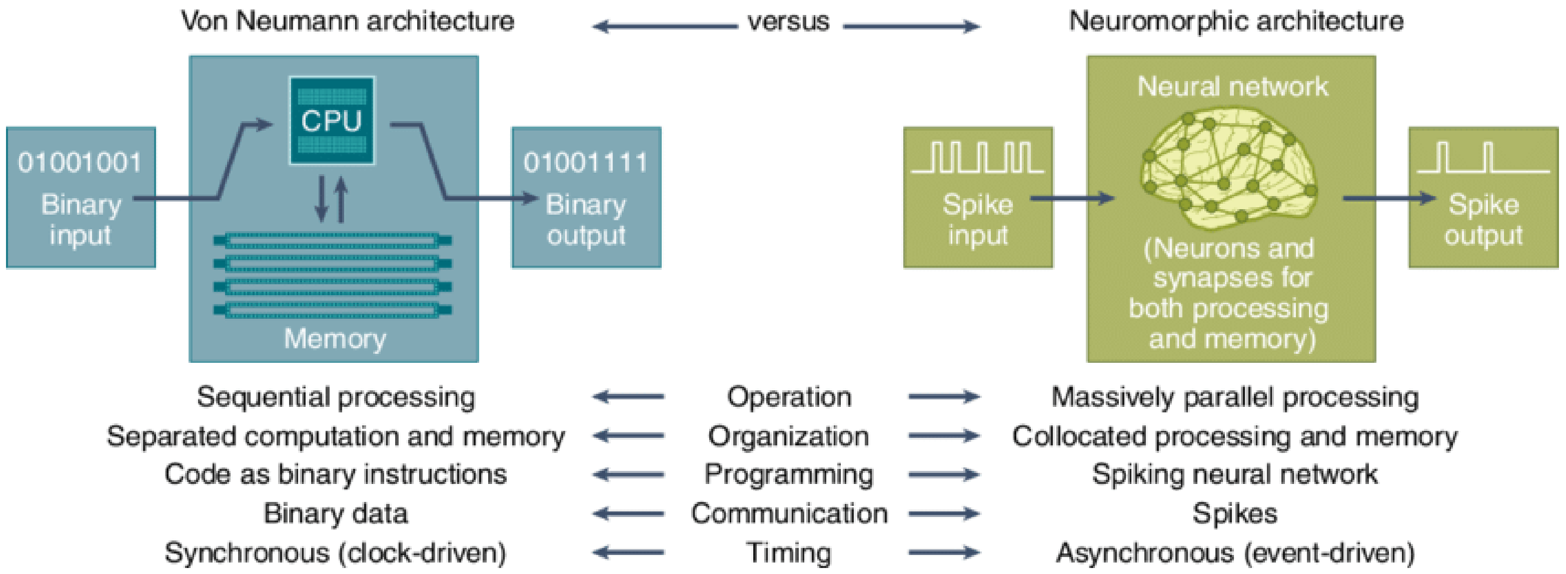


Spiking Neural Networks (SNNs)

- Biologically plausible neurons have a notion of charge and memory, that is reverse engineered to be implemented using memristors

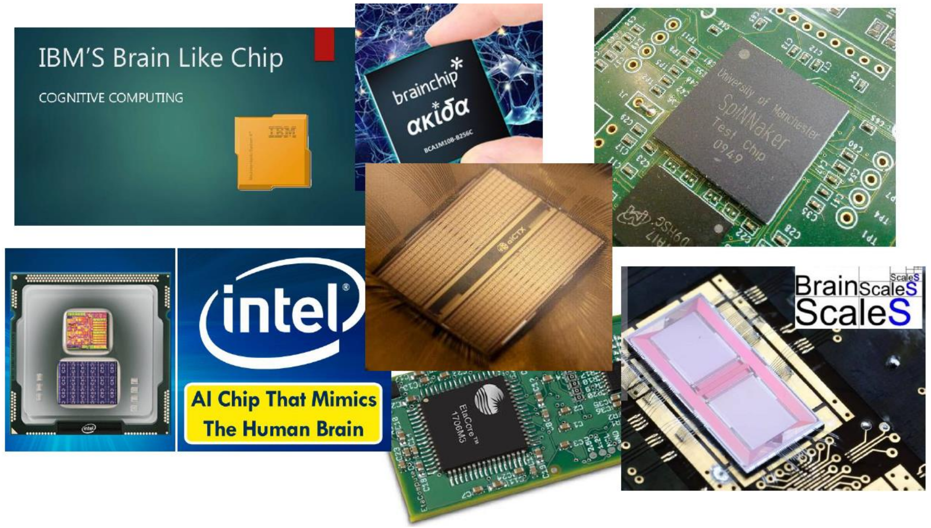
Source: S Sahoo, Y Song, « Spike Talk – Genesis and Neural Coding Scheme Translations », *Under preparation*, IEEE Trans. Smart Grid, 2024.

► Processing Alternatives Today



Proof-of-concept and commercial hardware implementations of SNNs have demonstrated significant energy savings as compared to ANNs

Human Brain Project EBRAINS

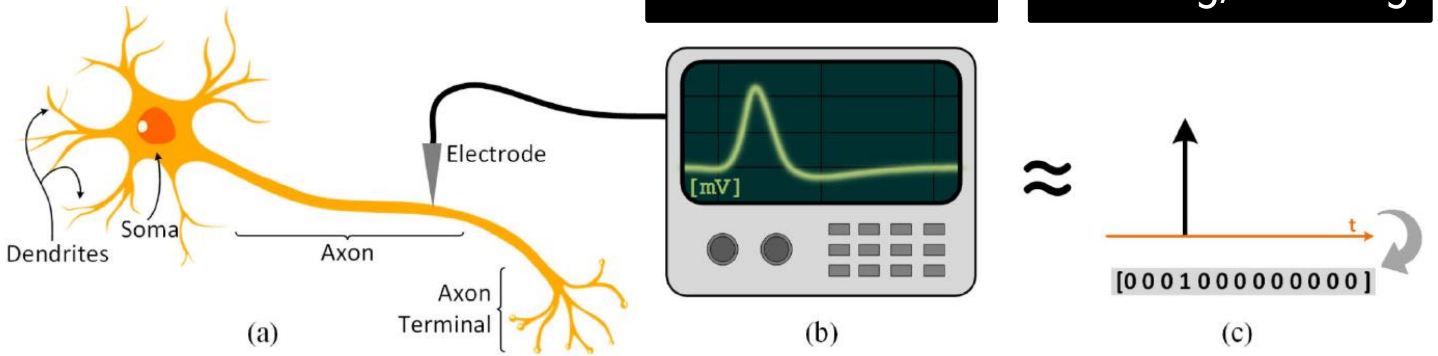


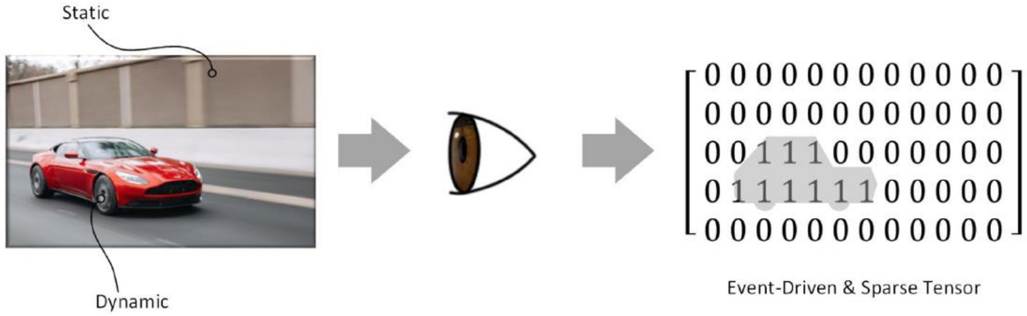
▶ Simple Examples

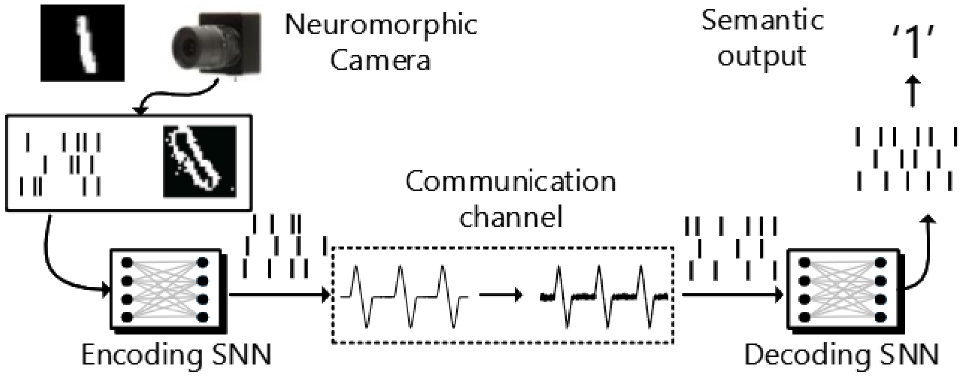
Data Translation

Encoding/Decoding

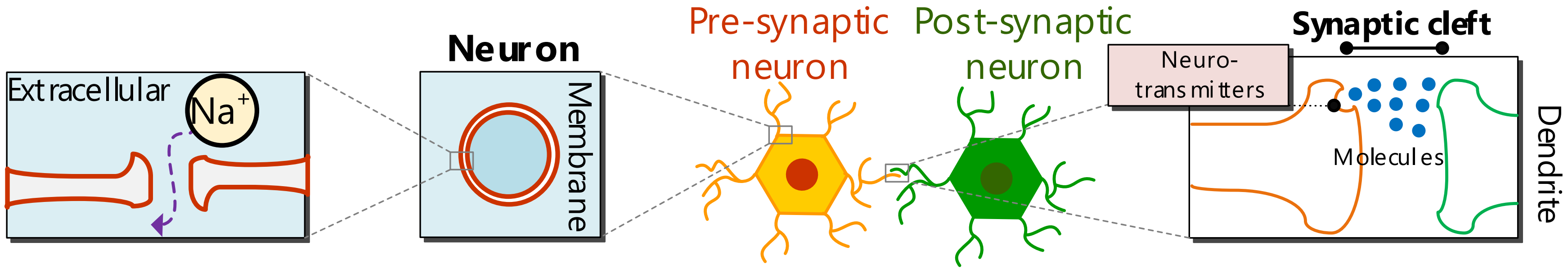
Source: Frenkel et al.: Bottom-Up and Top-Down Approaches for the Design of Neuromorphic Processing Systems, *Proc. Of the IEEE*, 2023.





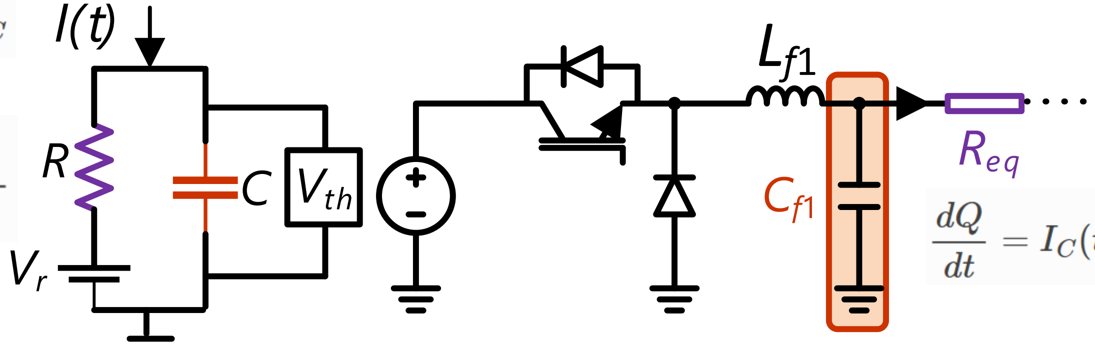


▶ Biologically Plausible Neurons

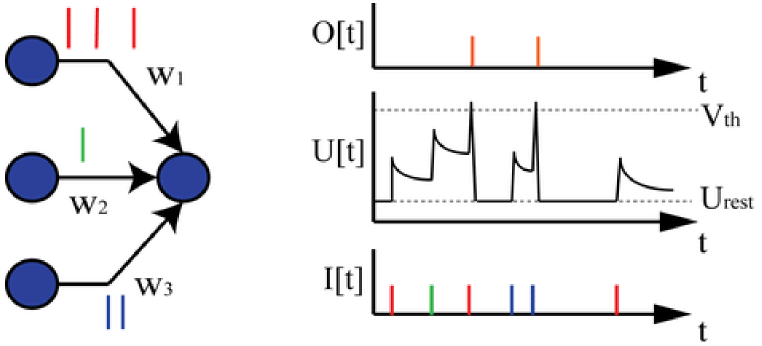


$$I_{\text{in}}(t) = I_R + I_C$$

$$I_R(t) = \frac{U_{\text{mem}}(t)}{R}$$



$$\frac{dQ}{dt} = I_C(t) = C\frac{dU_{\text{mem}}(t)}{dt}$$

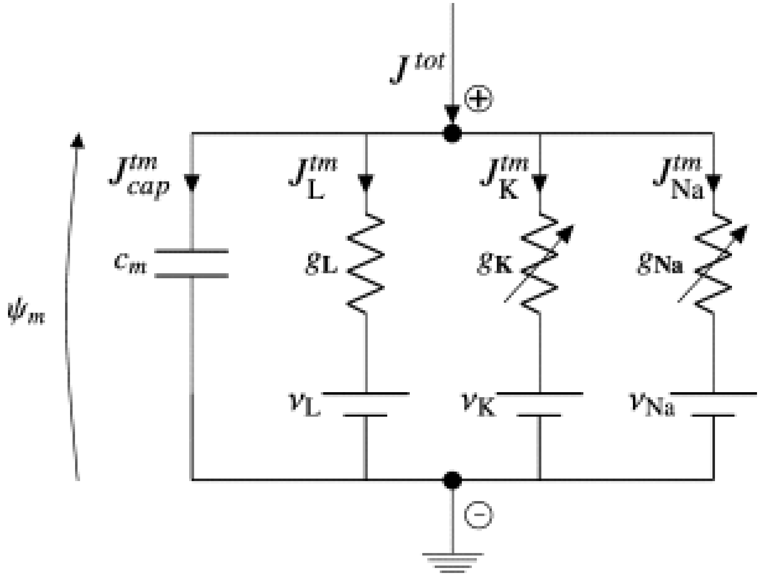


Leaky Integrate-and-Fire (LIF) Neuron

$$RC\frac{dU_{\text{mem}}(t)}{dt} = -U_{\text{mem}}(t) + RI_{\text{in}}(t)$$

Source: S Sahoo, Y Song, « Spike Talk – Genesis and Neural Coding Scheme Translations », *Under preparation*, IEEE Trans. Smart Grid, 2024.

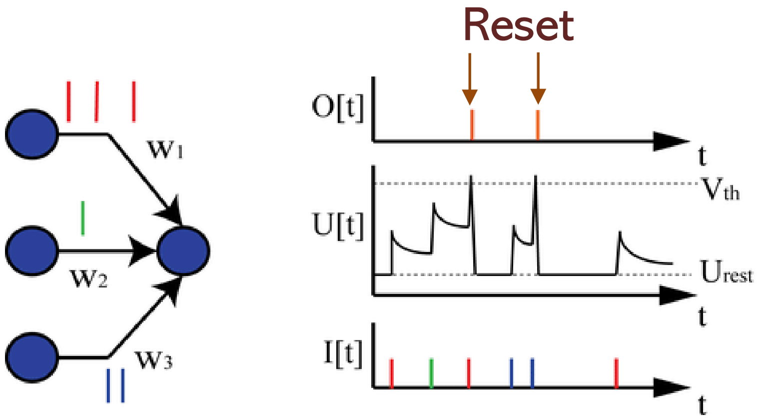
► Complicated Neuron Models and Reset Mechanism



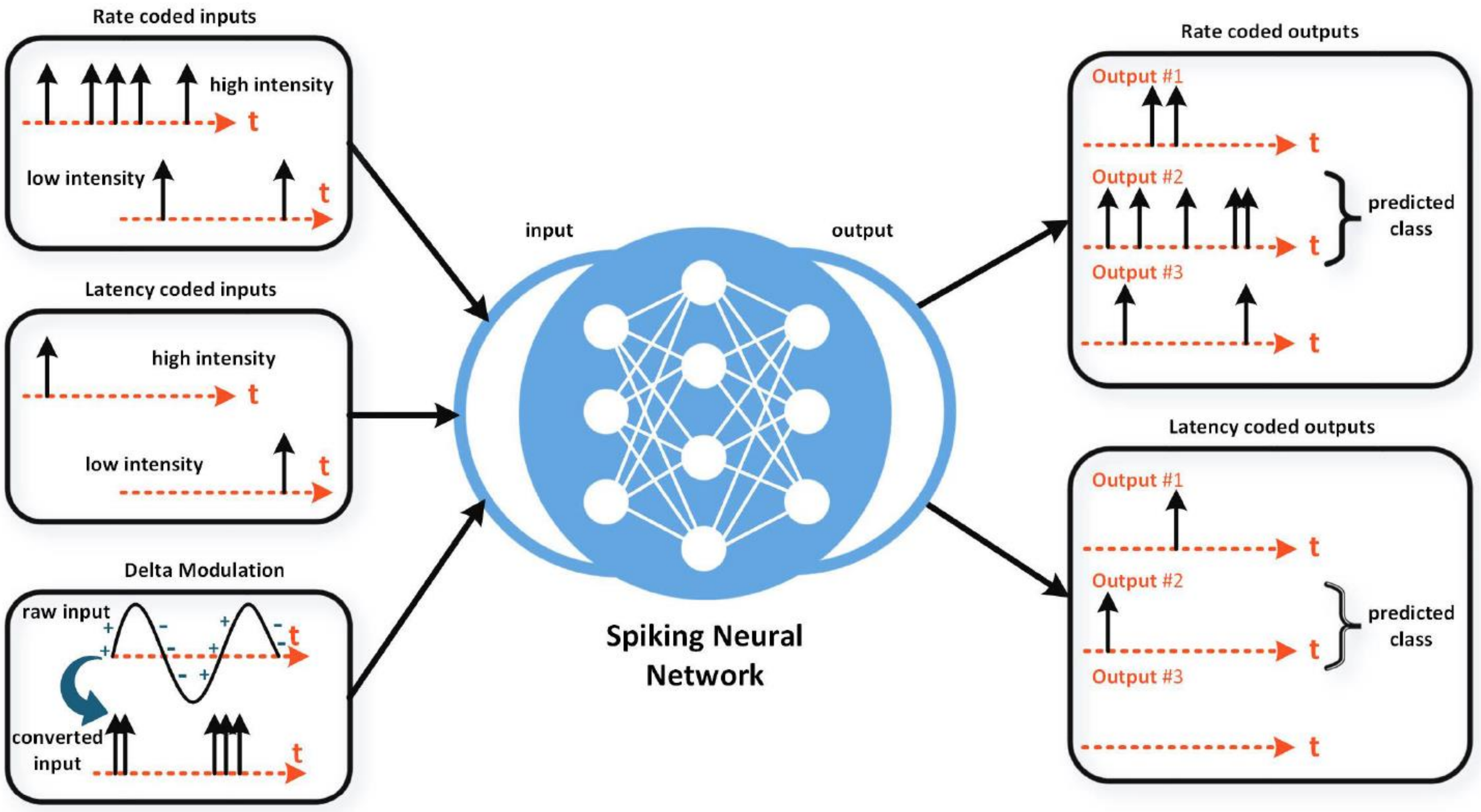
$$\sum_k I_k = g_{\mathrm{Na}}\, m^3 h\ (u - E_{\mathrm{Na}}) + g_{\mathrm{K}}\, n^4\ (u - E_{\mathrm{K}}) + g_L\ (u - E_L)$$

- Complicated (more accurate) model
- Poor computational efficiency – deployment issues with most hardware accelerators

Source: Wulfram Gerstner, Werner M. Kistler, Richard Naud, « Neuronal Dynamics: From Single Neurons to Networks and Models of Cognition », 2014.

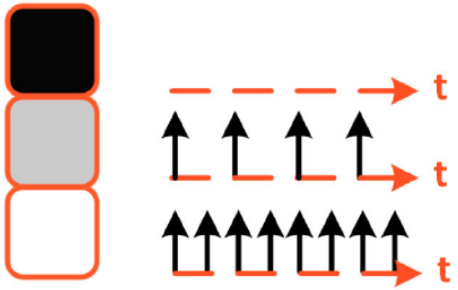


► Neural Coding Schemes



How to translate real-valued information into spikes?

- Input data to an SNN may be converted into a firing rate, a firing time, or the data can be delta modulated.
- The network itself may be trained to enable the correct class to have the highest firing rate or to fire first, among many other encoding strategies.



Source: Eshraghian et al.: Training SNNs Using Lessons From Deep Learning, *Proc. Of the IEEE*, 2023.

► Spike Timing Dependent Plasticity (STDP)

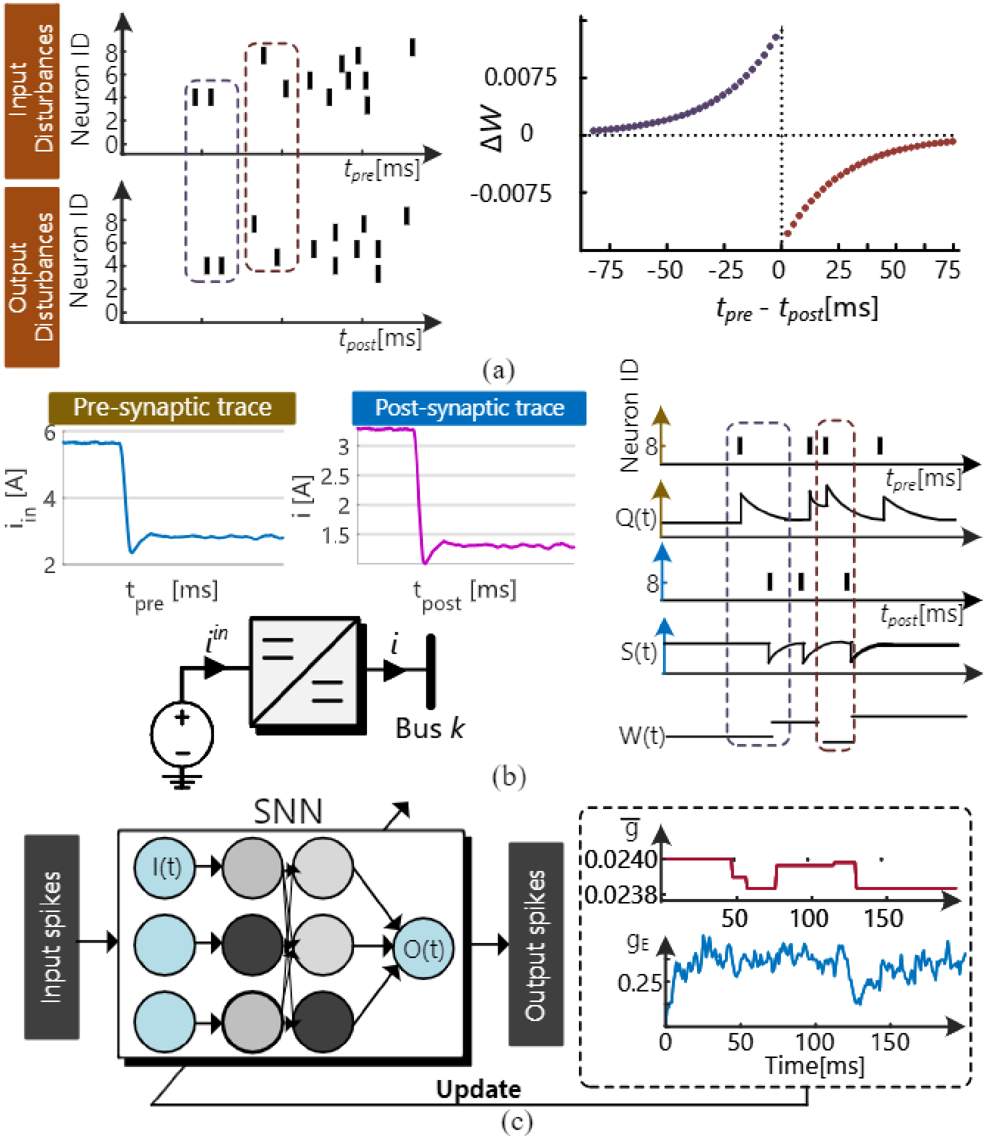
$$\Delta W = \begin{cases} A_+ e^{(t_{pre} - t_{post})/\tau_+} & (t_{post} > t_{pre}) \\ -A_- e^{-(t_{pre} - t_{post})/\tau_-} & (t_{post} < t_{pre}) \end{cases}$$

- The online weight update policy and its biological plausibility is explained by the Hebbian Principle: *"neurons that fire together wire together".*

$$\Delta W(t_{pre}) = S(t_{pre}) W(t_{pre})$$
$$\Delta W(t_{post}) = Q(t_{post}) W(t_{post})$$

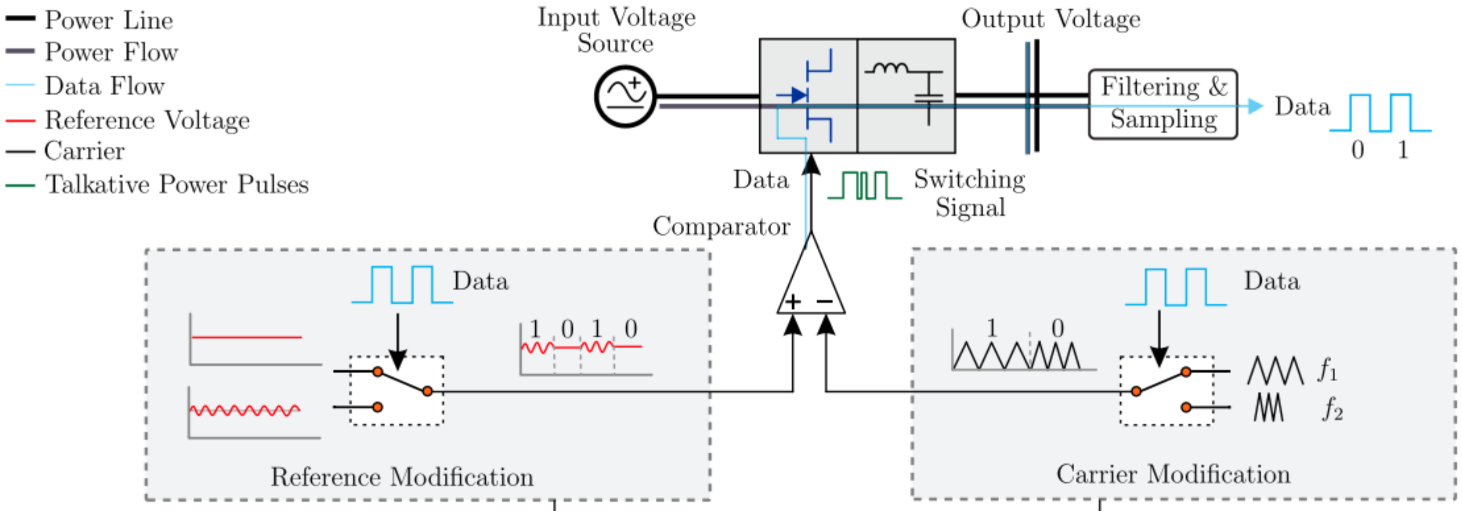
- If a pre-synaptic neuron fires just before a postsynaptic neuron, the connection between them is strengthened, often known as long-term potentiation (LTP).

- Otherwise, the connection is weakened, often known as long-term depression (LTD) of the same synapse.



Source: X Diao, Y Song, S Sahoo, Y Li, « Neuromorphic Event-Driven Semantic Communication in Microgrids» *IEEE Trans. Smart Grid*, 2024.

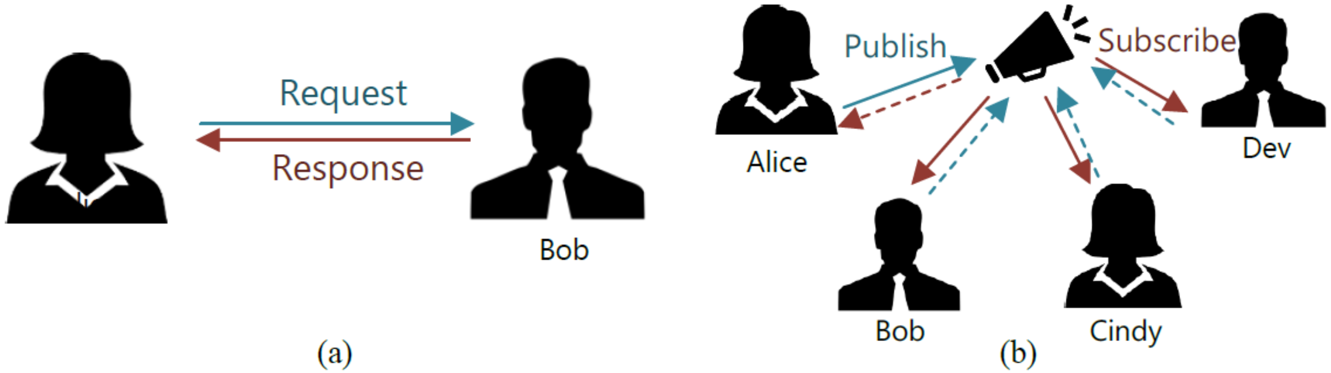
▶ Information Embedded in Power



Talkative Power

- Scalability
- Efficiency
- Transmission beyond electrically isolated stages
- Stakeholders' acceptance – grid codes?

Pioneering work by AAU researchers led by Prof. Petar Popovski – Power Talk



Inferential Communication

M. Liserre, H. Beiranvand, Y. Leng, R. Zhu and P. A. Hoeher, "Overview of Talkative Conversion Technologies," *IEEE Open Journal of Power Electronics*, vol. 4, pp. 67- 10.1109/OJPEL.2023.3237709.

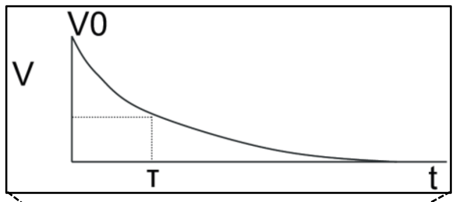
M. Angjelichinoski, Č. Stefanović, P. Popovski and F. Blaabjerg, "Power talk in DC micro grids: Constellation design and error probability performance," 2015 IEEE International Conference on Smart Grid Communications (SmartGridComm), Miami, FL, USA, 2015.

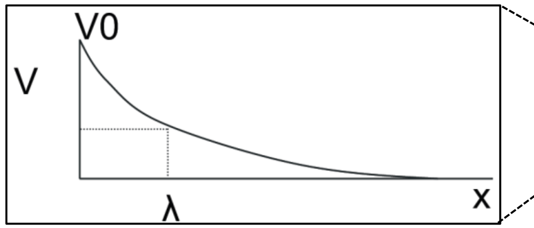
▶ Energy Systems

$$
\begin{bmatrix} \Delta P_s \\ \Delta P_r \\ \Delta Q_s \\ \Delta Q_r \end{bmatrix}^{(j)} =
\begin{bmatrix}
\frac{\partial P_s}{\partial \theta_s} & \frac{\partial P_s}{\partial \theta_r} & |V_s|\frac{\partial P_s}{\partial |V_s|} & N\frac{\partial P_s}{\partial N} \\
\frac{\partial P_r}{\partial \theta_s} & \frac{\partial P_r}{\partial \theta_r} & |V_s|\frac{\partial P_r}{\partial |V_s|} & N\frac{\partial P_r}{\partial N} \\
\frac{\partial Q_s}{\partial \theta_s} & \frac{\partial Q_s}{\partial \theta_r} & |V_s|\frac{\partial Q_s}{\partial |V_s|} & N\frac{\partial Q_s}{\partial N} \\
\frac{\partial Q_r}{\partial \theta_s} & \frac{\partial Q_r}{\partial \theta_r} & |V_s|\frac{\partial Q_r}{\partial |V_s|} & N\frac{\partial Q_r}{\partial N}
\end{bmatrix}^{(j)}
\begin{bmatrix} \Delta \theta_s \\ \Delta \theta_r \\ \frac{\Delta |V|_s}{|V|_s} \\ \frac{\Delta N}{N} \end{bmatrix}
$$

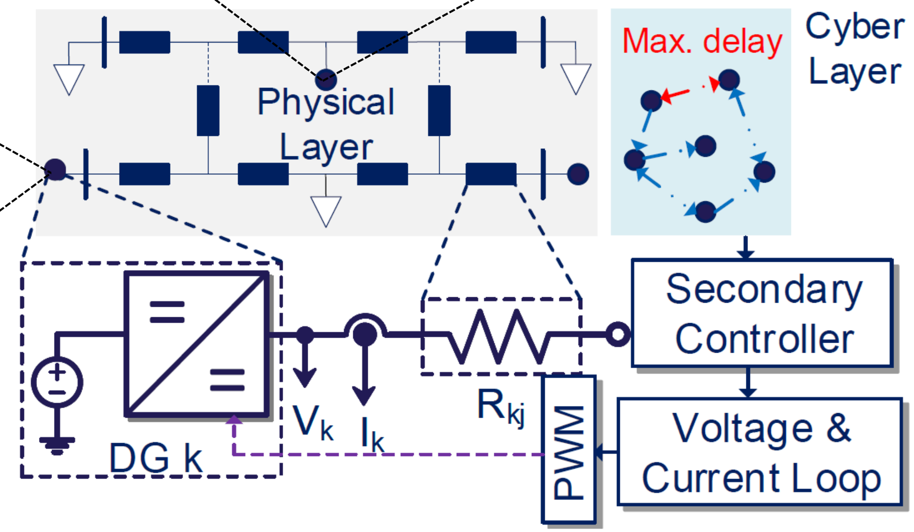
Spatio-temporal pattern exploration

Temporal patterns in voltages

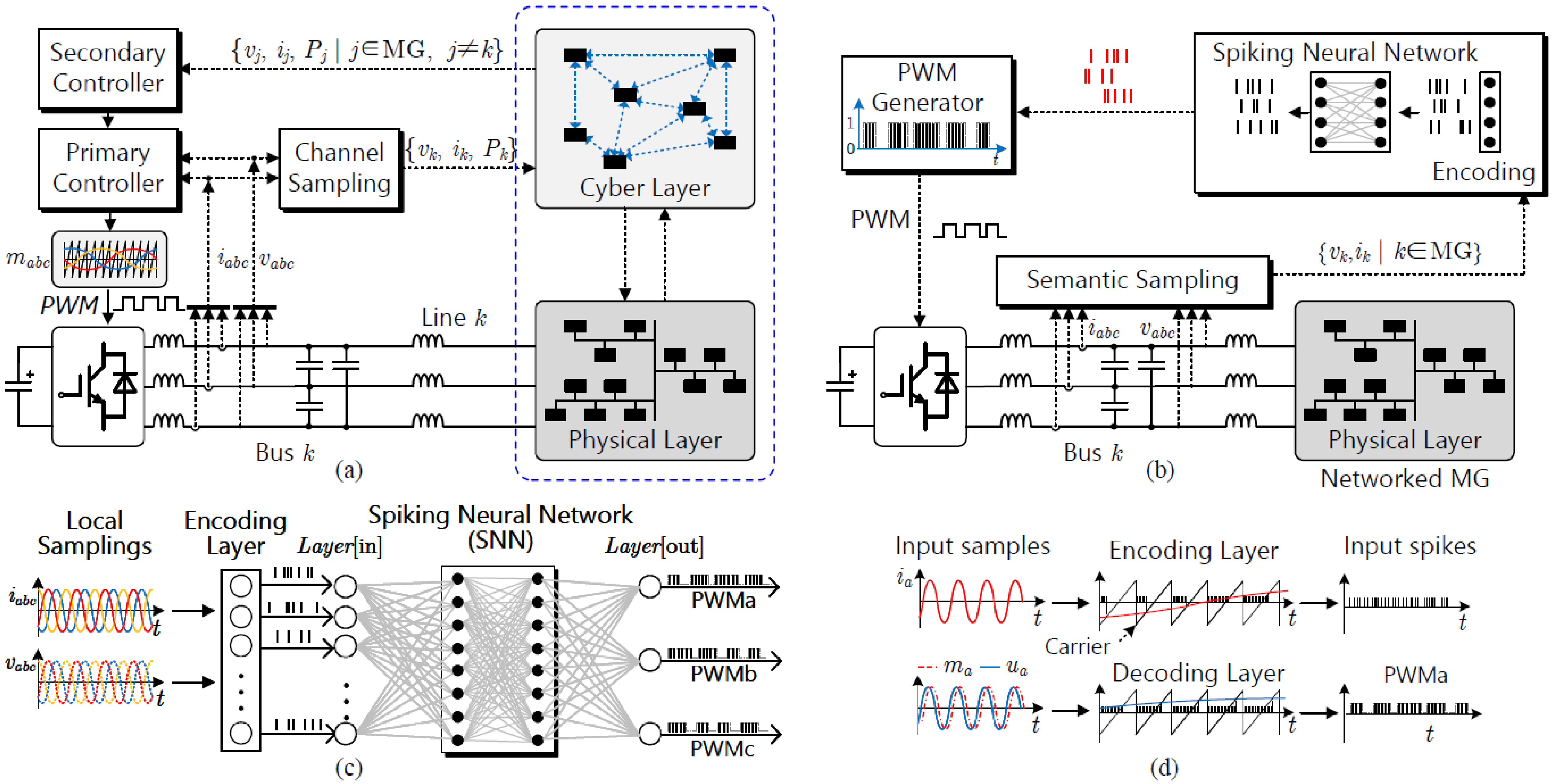




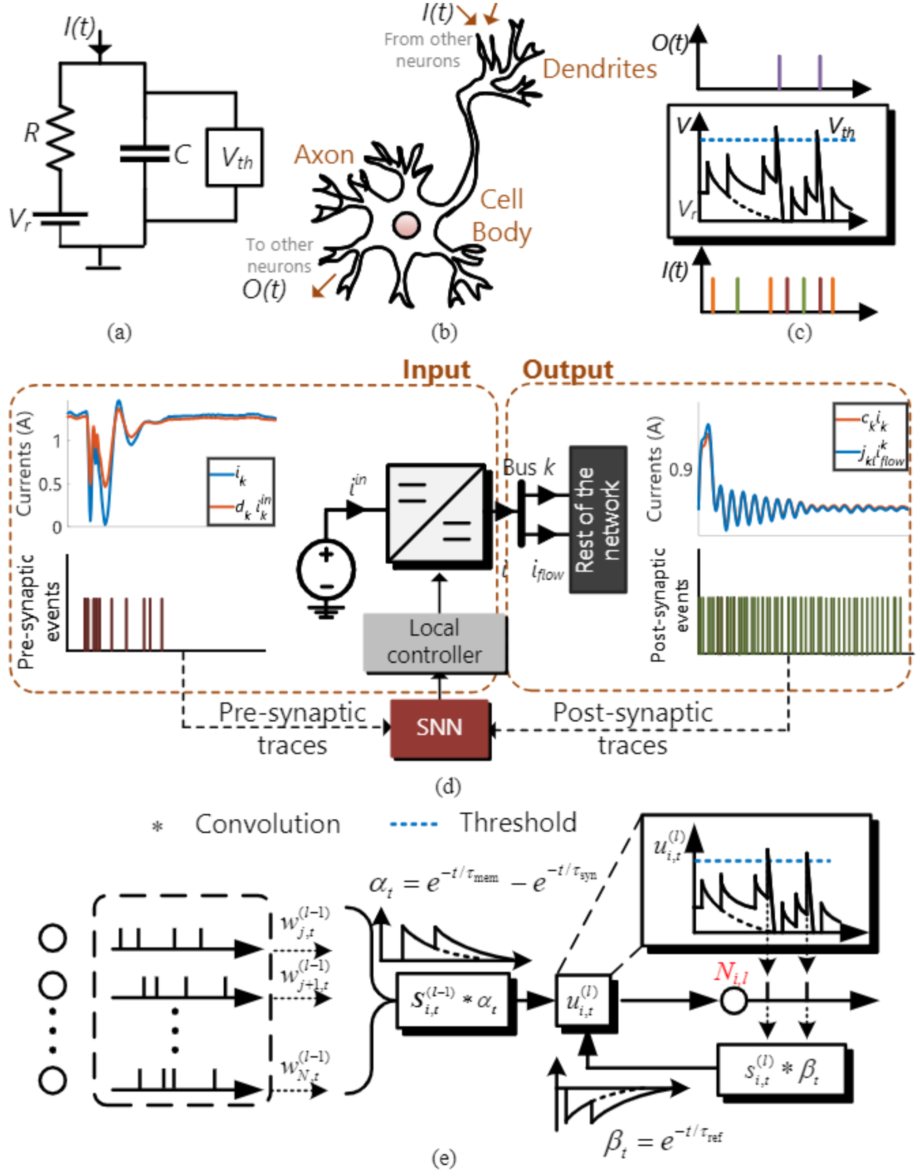
Spatial patterns in voltages



▶ Re-inventing Cyber-Physical Architecture



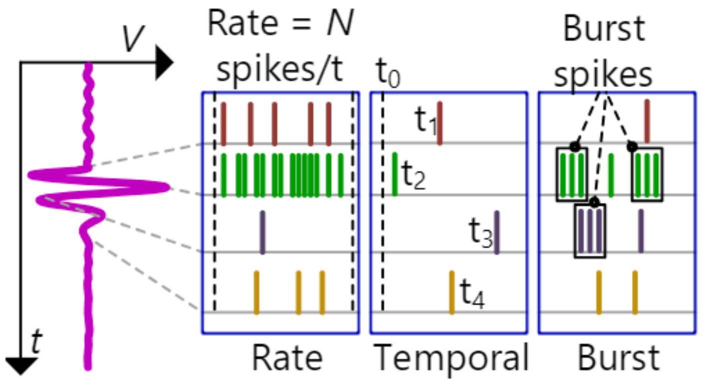
▶ Spiking Neuron as Energy Source

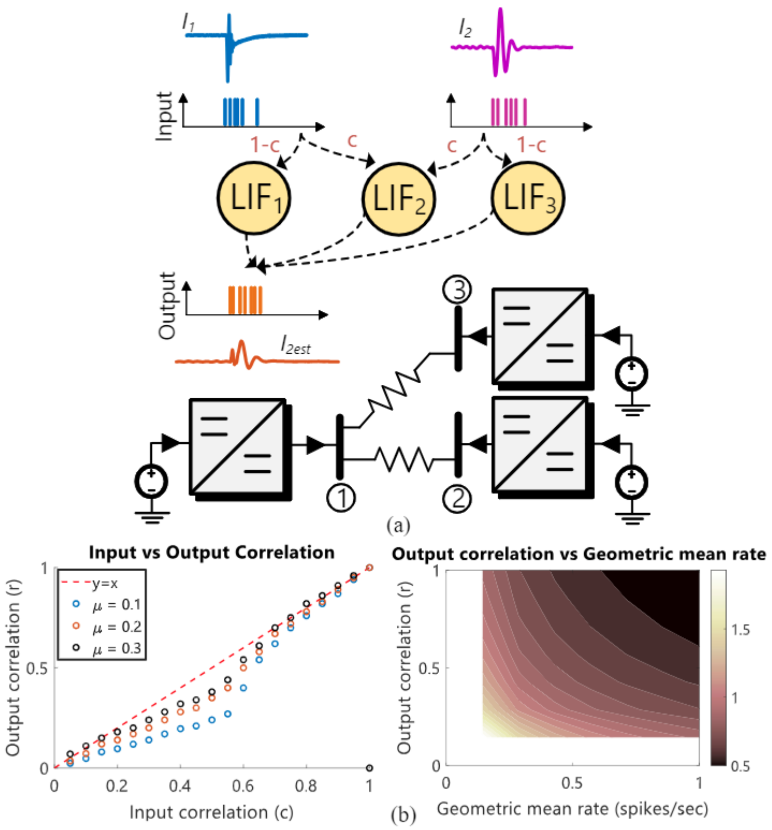


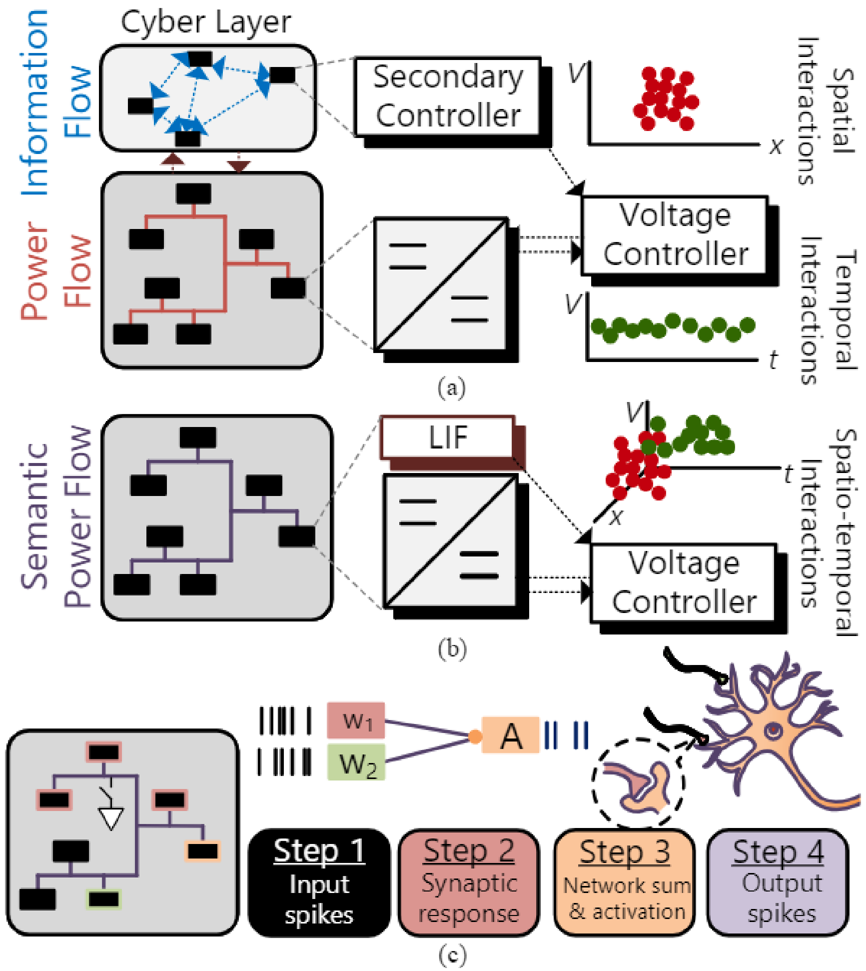
- We model each source as a LIF neuron
- It can respond to both input and output disturbances
- Only the remote sources will respond to a given disturbance based on the voltage fluctuations and its spatial decay
- STDP to change the conductance of the modeled neuron and change power generation
- Multi-agent networked control, adaptation, protection, flexibility is possible with minimal energy consumption per inference

► Spike Talk

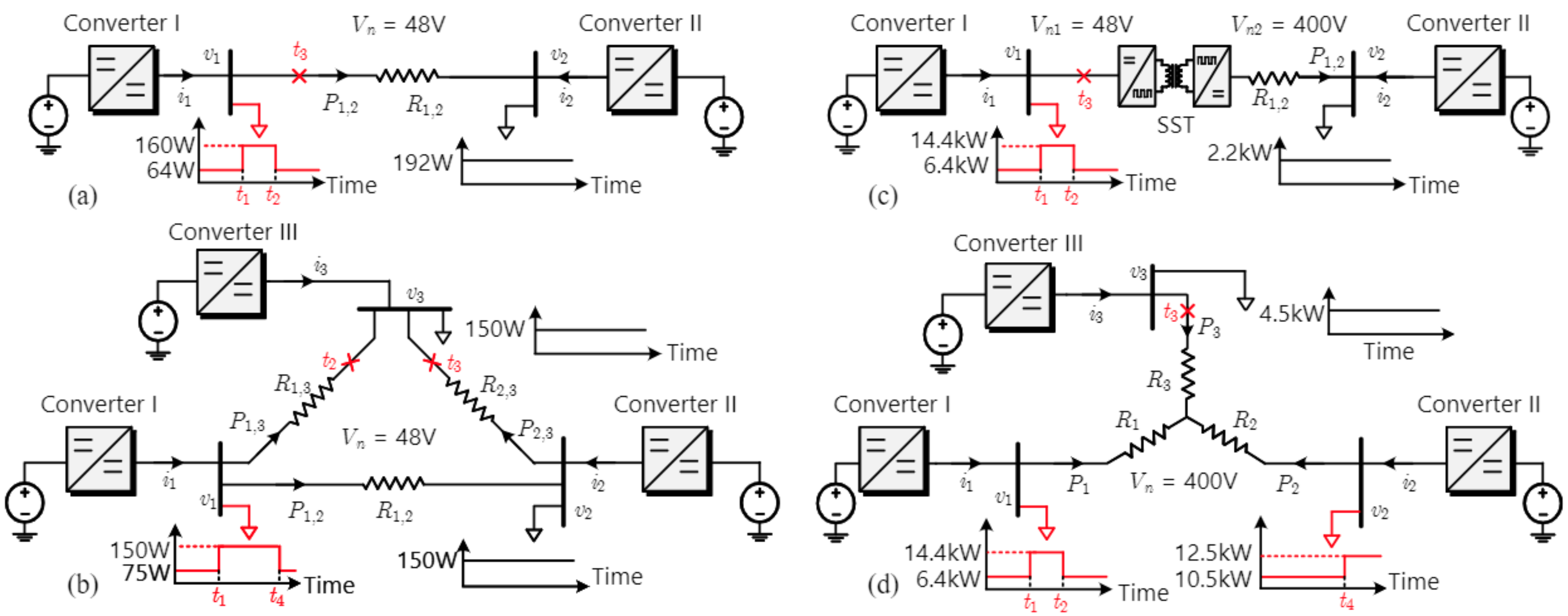
- No communication – no exogeneous path arrival for attackers
- Sparsity of signals acts as a leverage
- Easy adaptation
- Online training

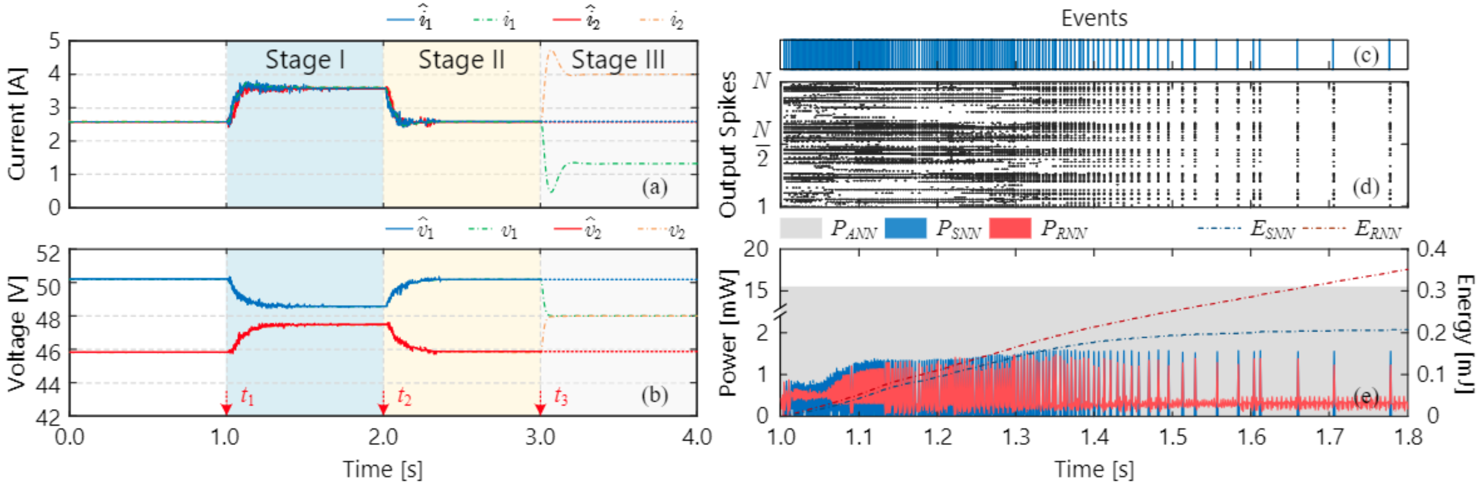






► Performance Evaluation





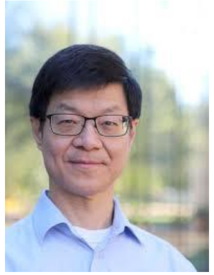
Source: X Diao, Y Song, S Sahoo, Y Li, « Neuromorphic Event-Driven Semantic Communication in Microgrids» *IEEE Trans. Smart Grid*, 2024.

► Closing Remarks

- Accuracy and Versatility – Big Questions Going Forward
- Innovations in Neuromorphic Hardware
- Cost – Big Limitation
- From pJ of computation concerns to kW of energy loss – how will this neural implant be projected by energy stakeholders?

Open Course on **Neuromorphic Computing in Power Electronics** (certification to be provided by IEEE PELS)

- **8 video lectures – computational neuroscience, coding schemes, power electronic integration**
- **Notes, exercises**
- **FAQs**



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Yubo Song

Xiaoguang Diao

Nordic Energy Research

► Key References

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