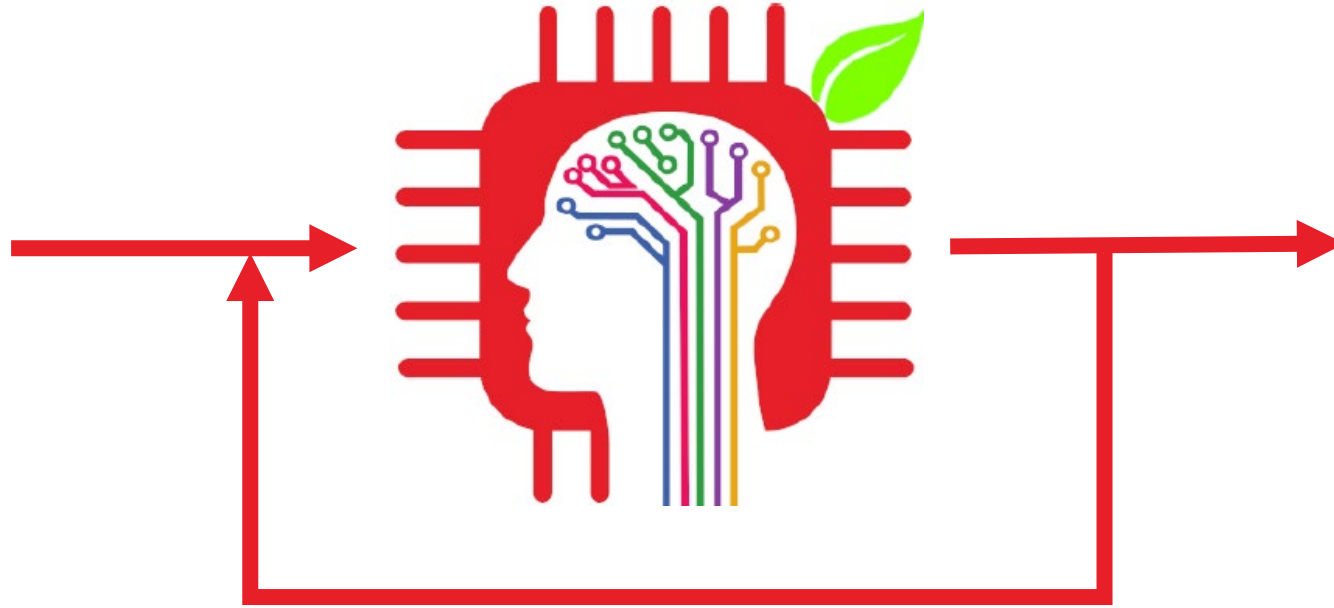


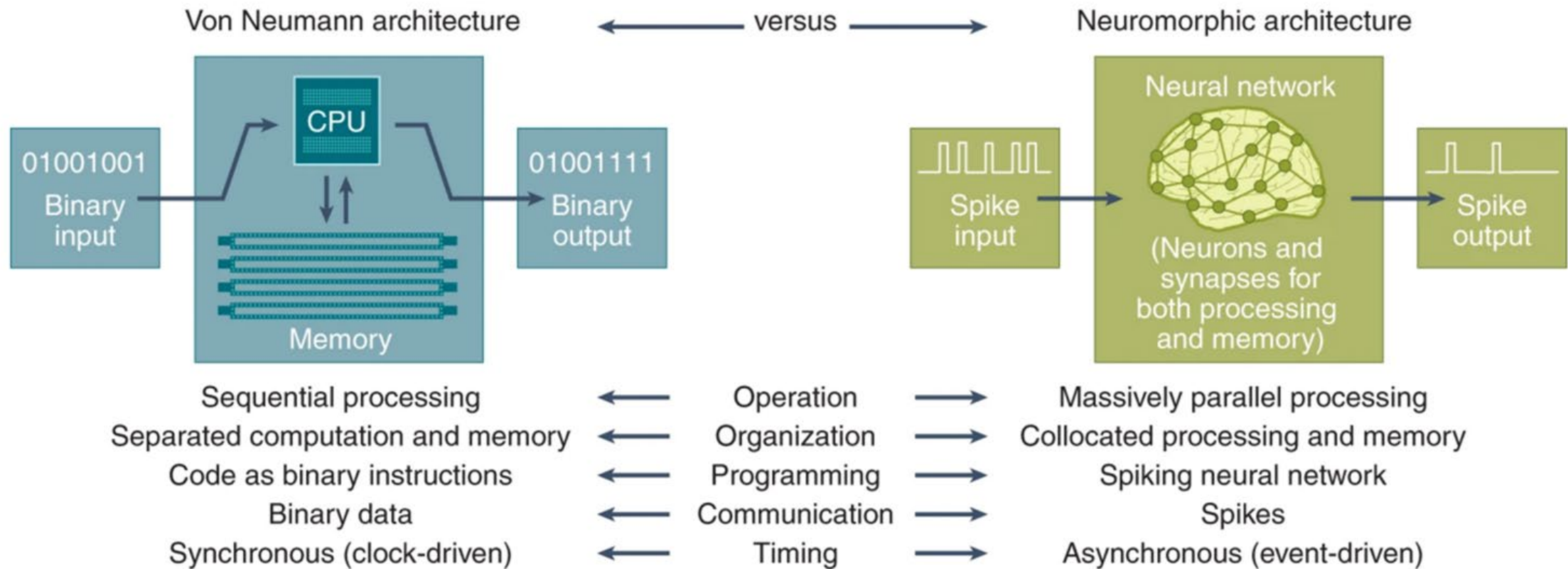


Neuromorphic Feedback Control for Power Electronics Systems

Prof. Dr. Cristian Axenie SMIEEE

Neuromorphic Feedback Control for Power Electronics Systems

A new computing paradigm



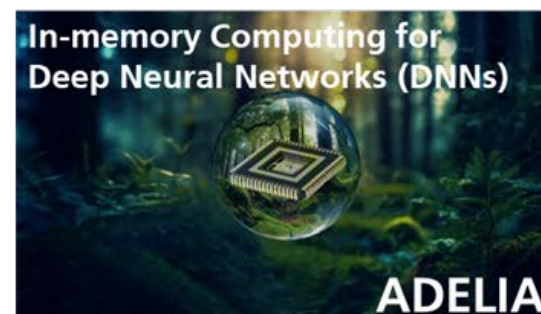
<https://www.nature.com/articles/s43588-021-00184-y>

A new computing paradigm



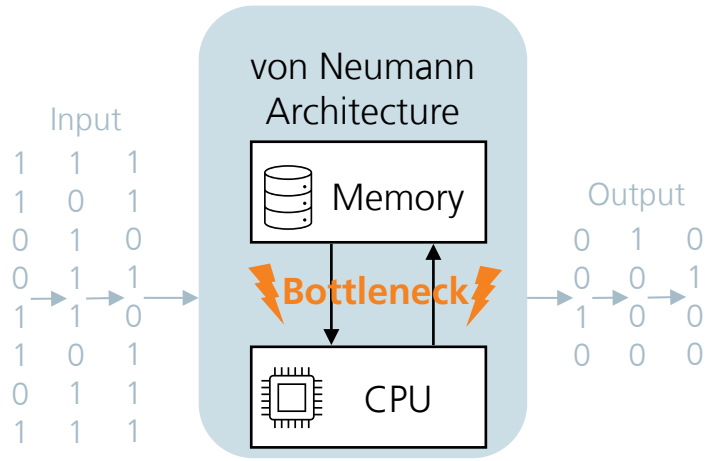
Neuromorphic chip for ultrafast ($< 20 \mu$ s) and energy-efficient processing of low-dimensional time series signals (smart signal processing, closed-loop control systems)

*) In Collaboration with Fraunhofer EMFT



MultiCore accelerator based on analog in-memory computing for ultra-low power computing (140 μ W per core) in Wearables, IoT und Healthcare

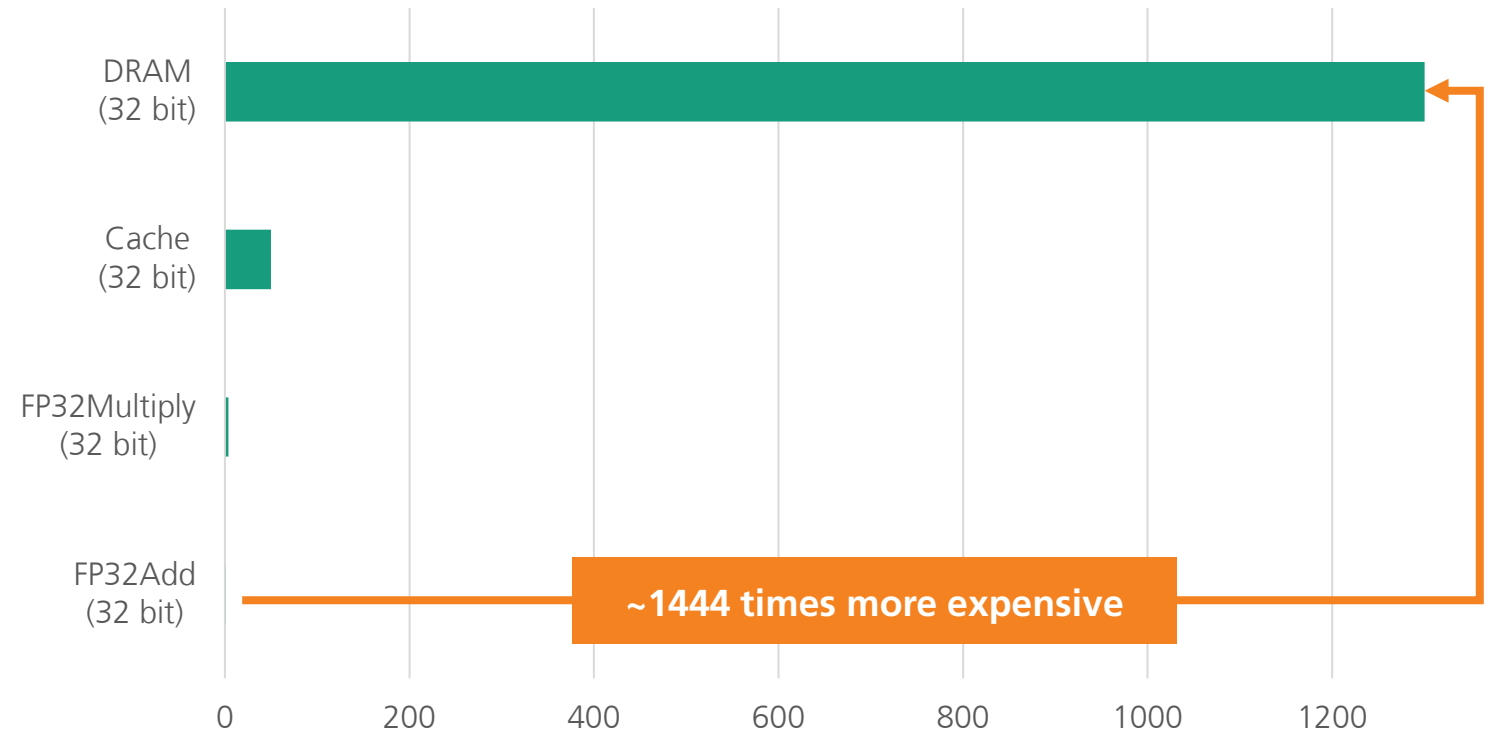
Limits of Traditional Computation Paradigms



Traditional Computation Paradigm

- Separated computation and memory
- Limited compute parallelism
- Digital compute signals
- Dense data (continuous values and synchronous data stream)

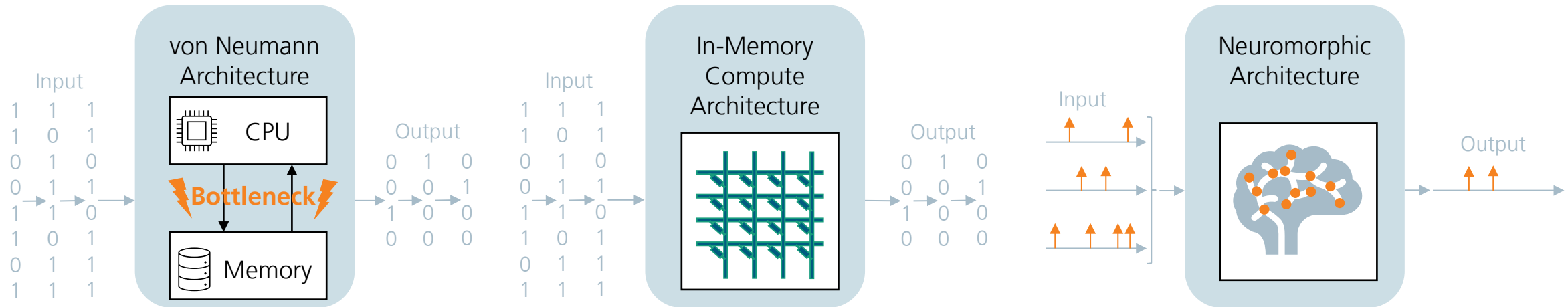
Typical Energy Consumption in 45nm Technology [in pJ]



Source: Horowitz, M. *Computing's Energy Problem and What We Can Do About It*, ISSCC 2014

→ Moving data from memory to CPU is energy intensive and limited by the bandwidth between memory and CPU

Overcoming the von Neumann Bottleneck

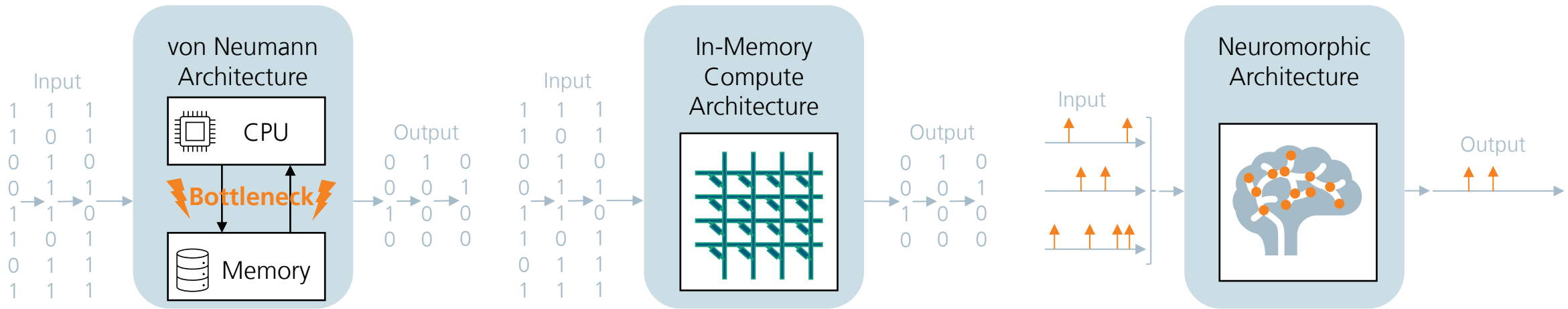


Traditional Computation Paradigm

In-memory Computing

Neuromorphic Architecture

Key Differences between Compute Paradigms



Traditional Computation Paradigm

- Separated computation and memory
- Limited compute parallelism
- Digital compute signals
- Dense data (binary, continuous and synchronous data stream)

In-memory Compute

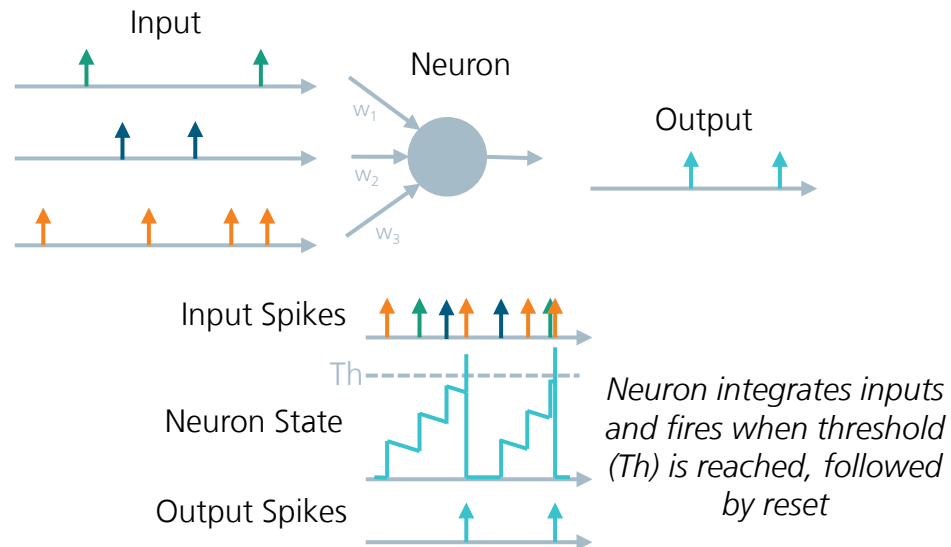
- Collocated computation and memory
- Massive compute parallelism
- Mixed-signal (digital/analog) compute signals possible
- Dense data (continuous values and synchronous data stream)

Neuromorphic Architecture

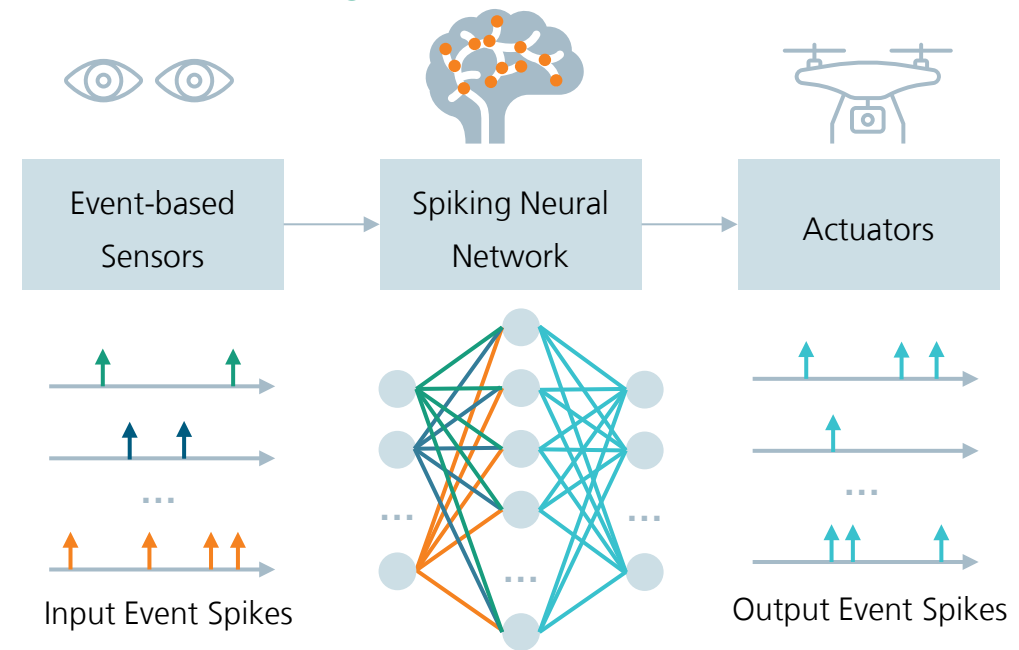
- Collocated computation and memory
- Massive compute parallelism
- Mixed-signal (digital/analog) compute signals possible
- Sparse data (spiking, event-based and asynchronous data stream)

Neuromorphic Computing – Working Principle

Neuron Model



Spiking Neural Network (SNN)



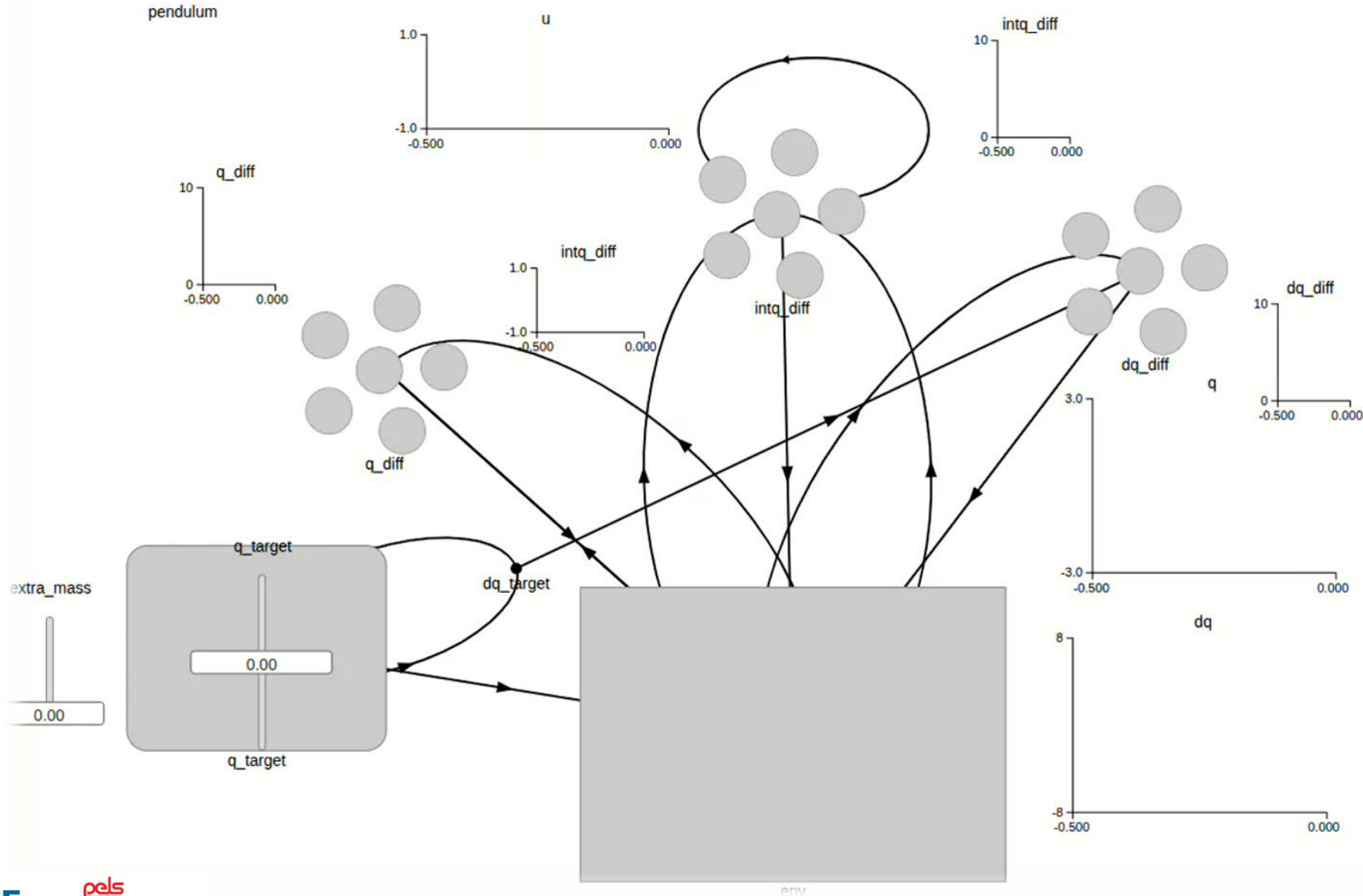
- Neurons collocate weights (w_i) and compute logic and allow mixed-signal implementations → **SNNs allow increased power efficiency**
- SNNs exploit sparsity (inputs and weights are not dense) → **SNNs require less data movement than DNNs**
- Bio-inspired compute algorithms allow beyond-Moore compute concepts (e.g. fully parallel designs) → **Reduced reliance on Moore's law**

Neuromorphic Feedback Control for Power Electronics Systems

Neuromorphic Feedback Control: An introduction



Neuromorphic Feedback Control: An introduction



Nengo core

NengoGUI

NengoDL

NengoSPA

NengoExtras

Nengolib

KerasSpiking

PyTorchSpiking

NengoFPGA

NengoLoihi

NengoOCL

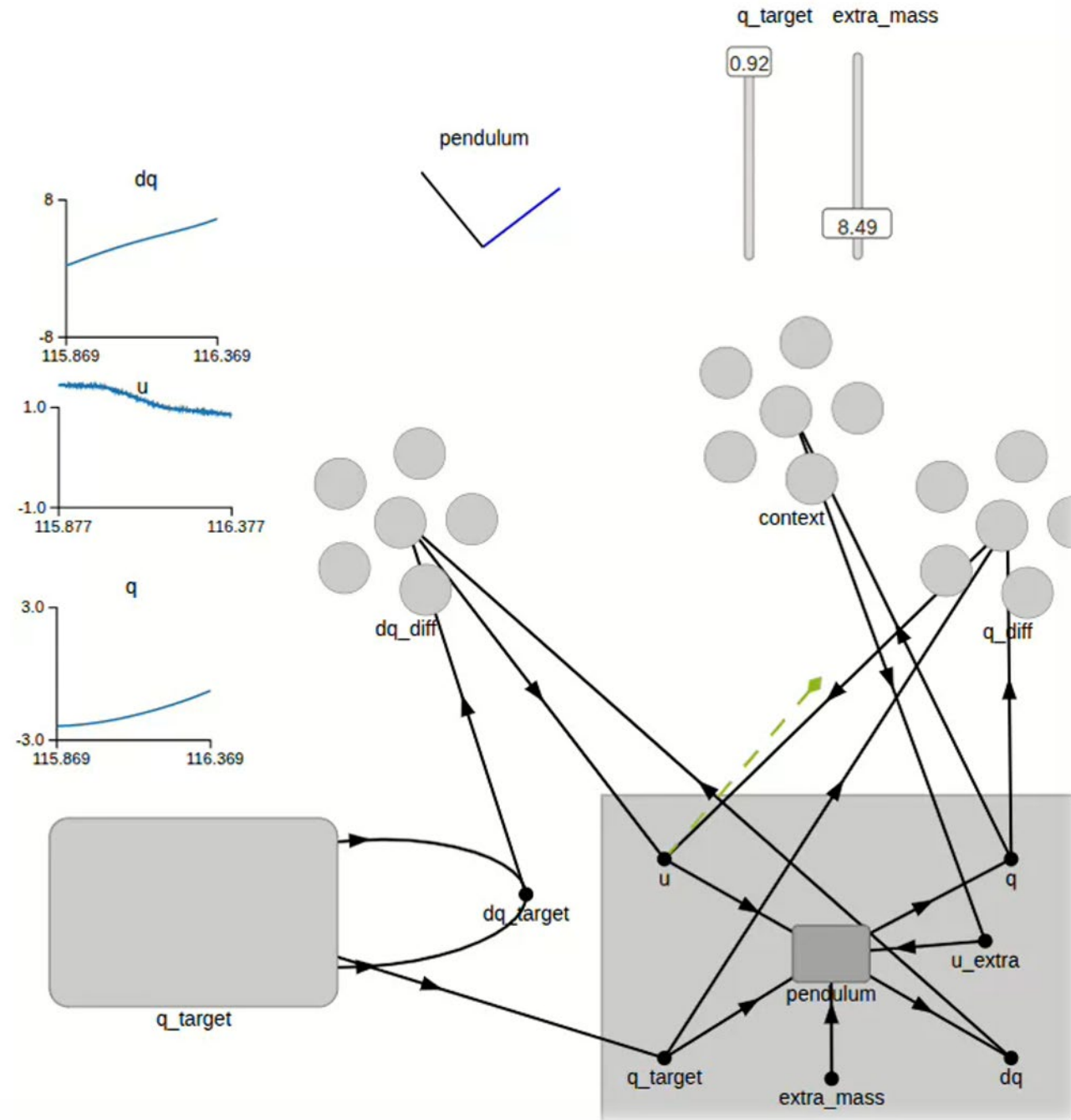
NengoSpiNNaker

NengoMPI

Neuronal PID Controller

Nengo

Neuromorphic Feedback Control: An introduction



Nengo core

NengoGUI

NengoDL

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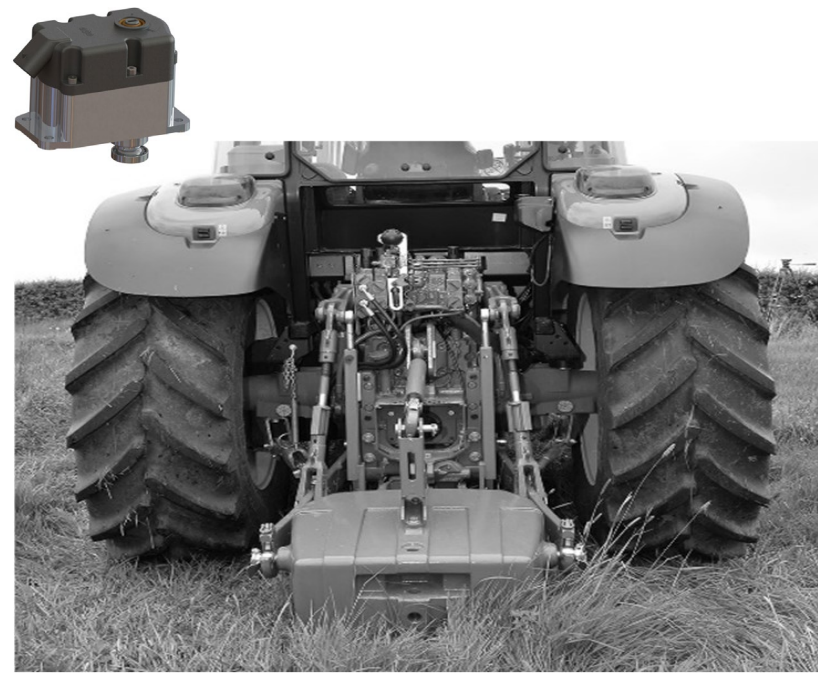
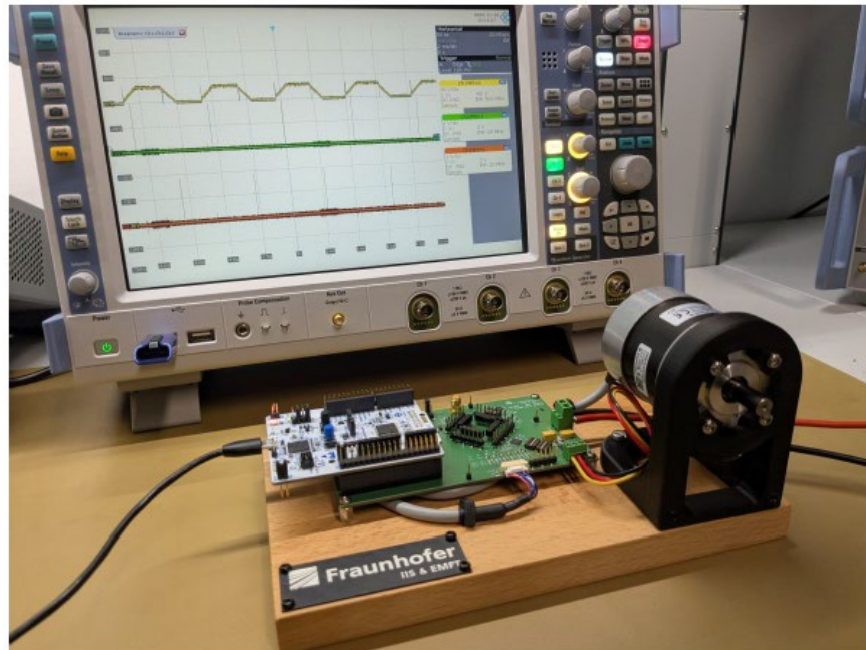
NengoMPI

Learning
PD Controller

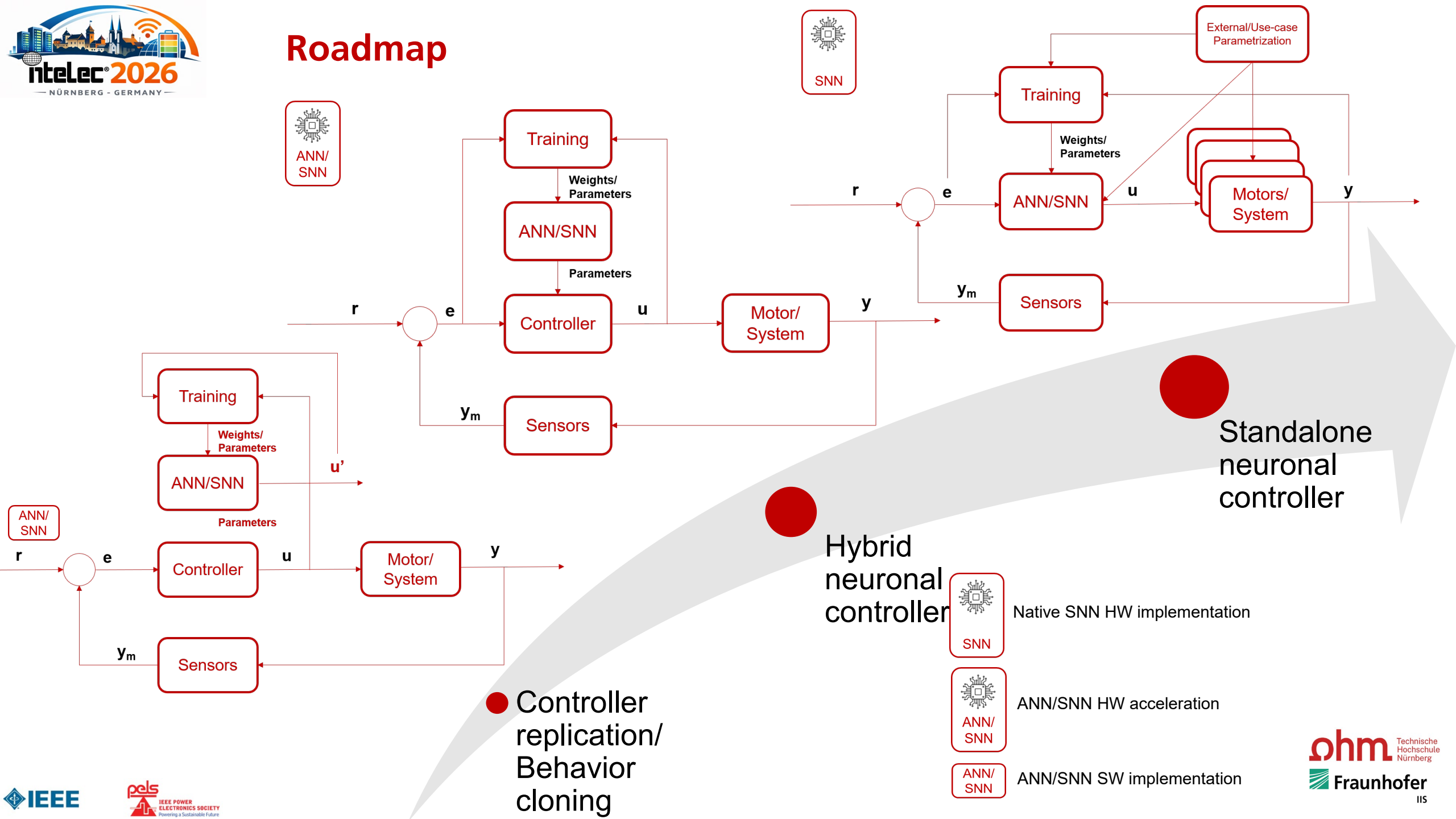
Nengo

Neuromorphic Feedback Control for Power Electronics Systems

Power electronics systems

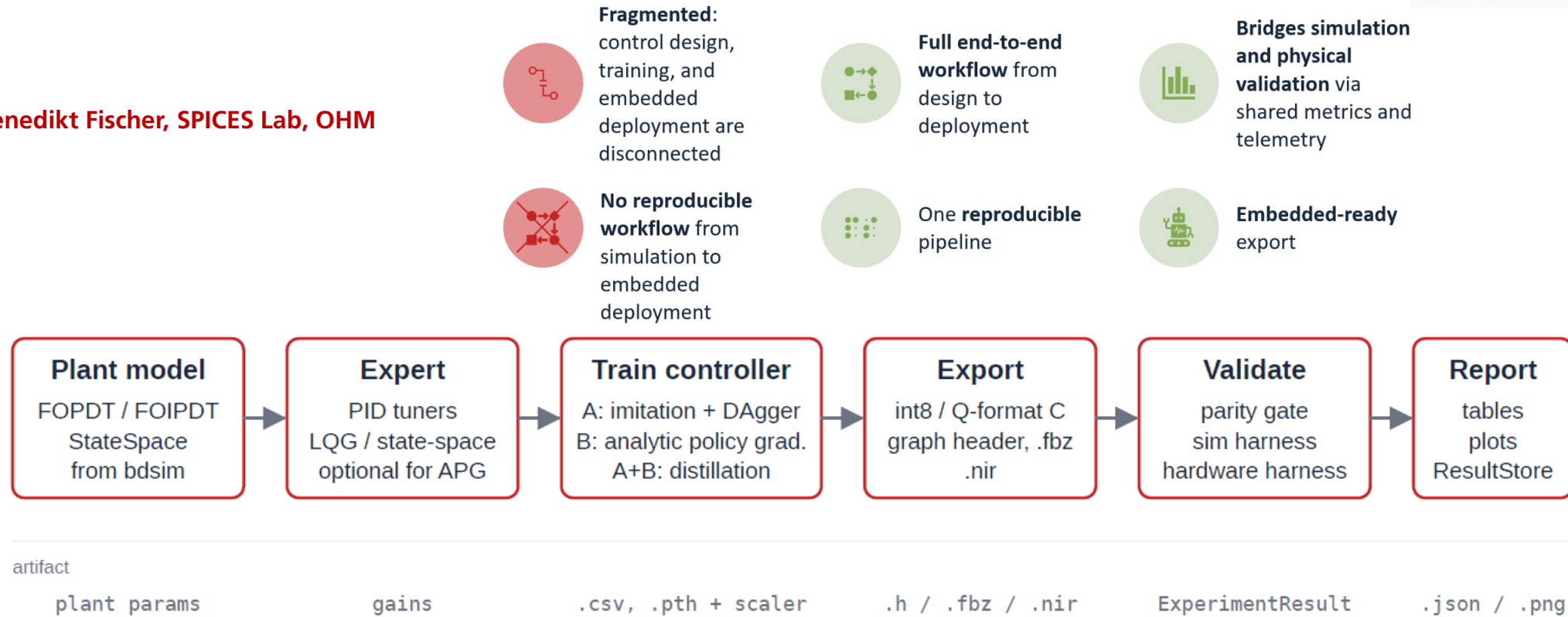


Roadmap



Toolkit for neural and neuromorphic control design and deployment on resource-constrained devices

Collaboration: Benedikt Fischer, SPICES Lab, OHM



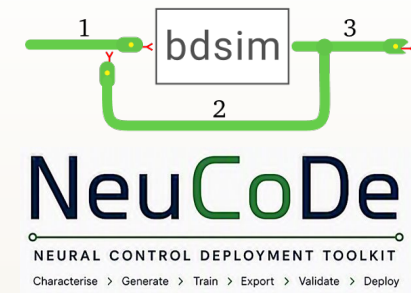
Every stage reads and writes files, so a run can start at any stage (README: staged, resumable pipeline).

- Each stage reads and writes artifacts, so you can **enter at any stage**: tune only, retrain from a saved dataset, re-export a saved model, or re-score a saved trajectory.
- The same controller object is used in simulation and on hardware; only the harness changes.

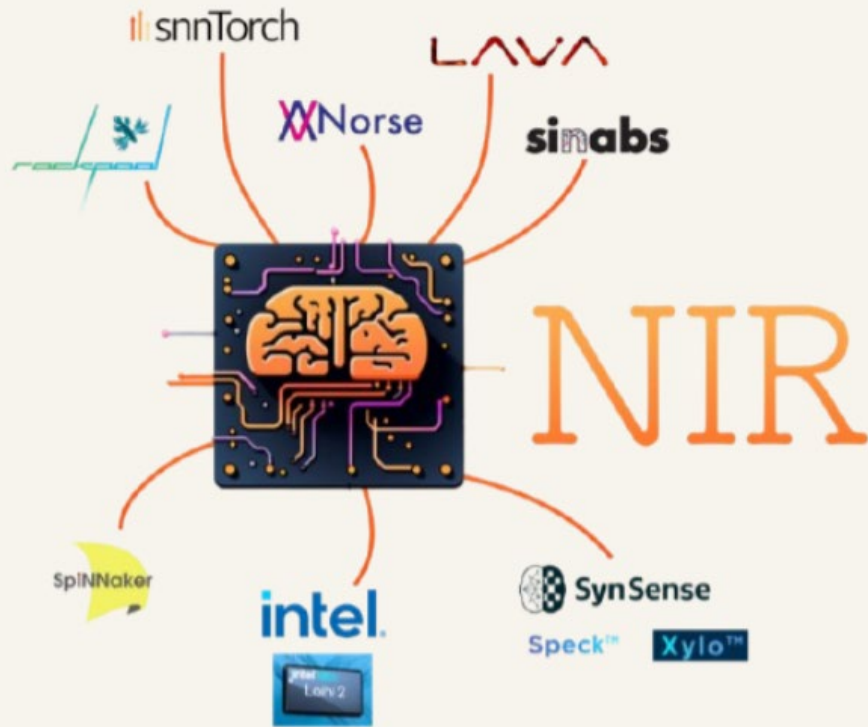
Acknowledgments:

This work was funded by the STAEDTLER-Stiftung Grant No. WW/ar 09/25 (Project NeuroPower) and partially by the Fraunhofer Research Programs Grant No. Attract 40-11894

Toolkit for neural and neuromorphic control design and deployment on resource-constrained devices



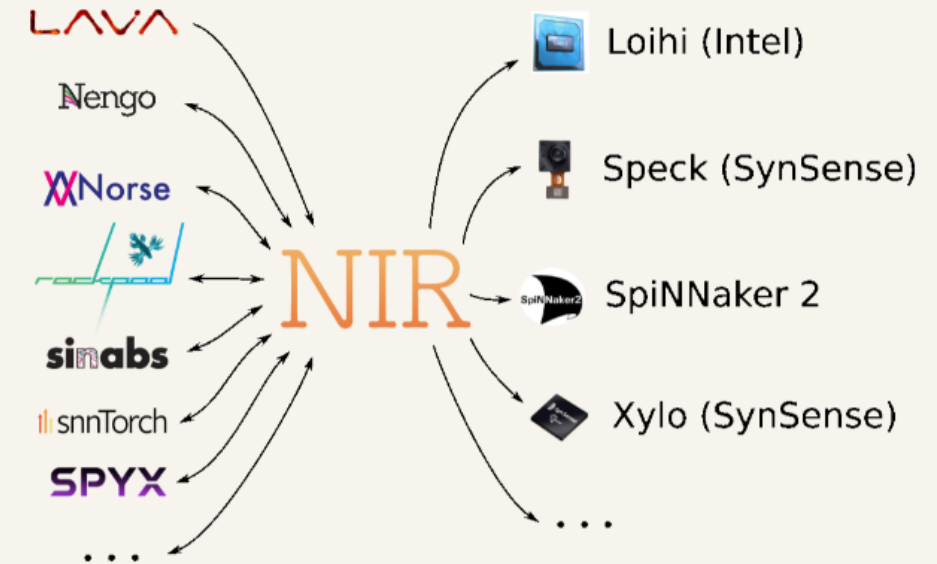
Collaboration: Benedikt Fischer, SPICES Lab, OHM



Simulators

Hardware platforms

Interoperability



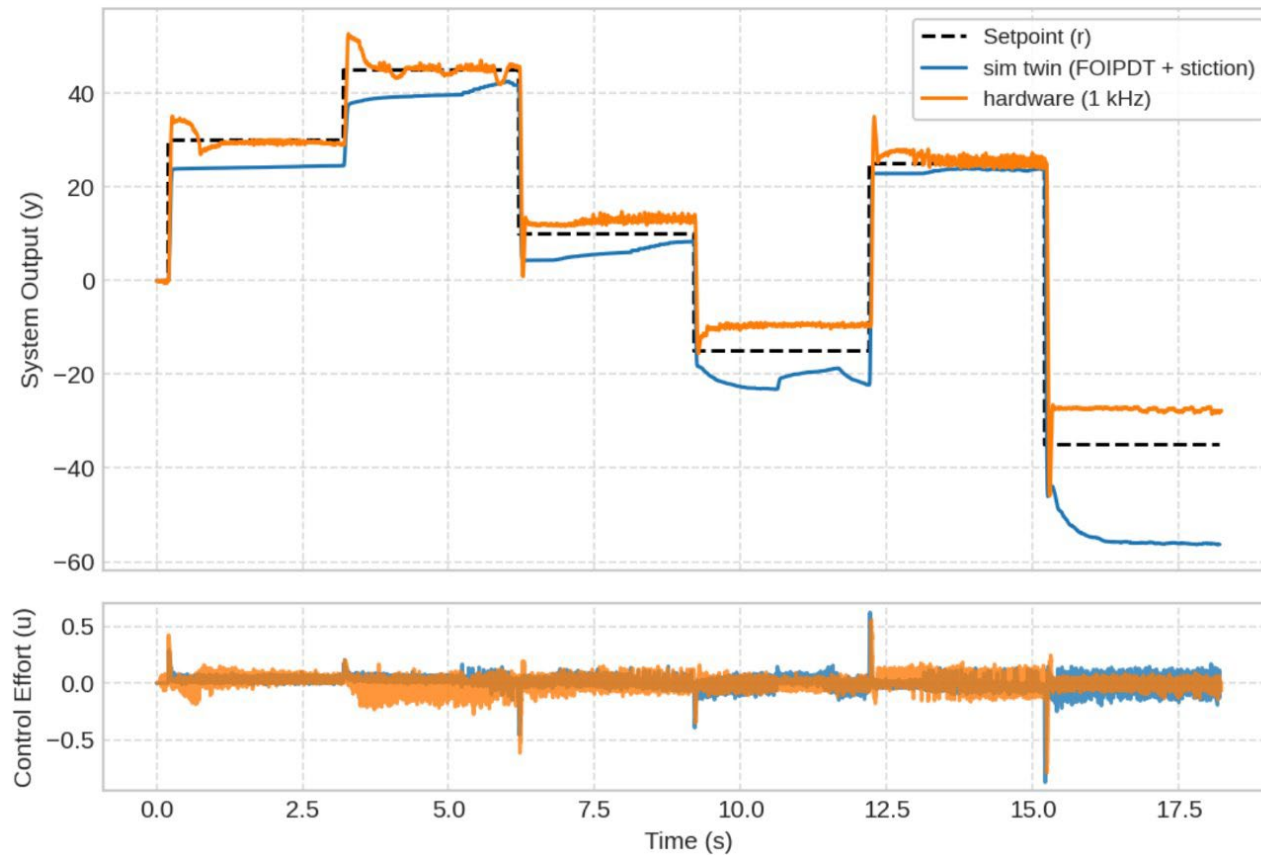
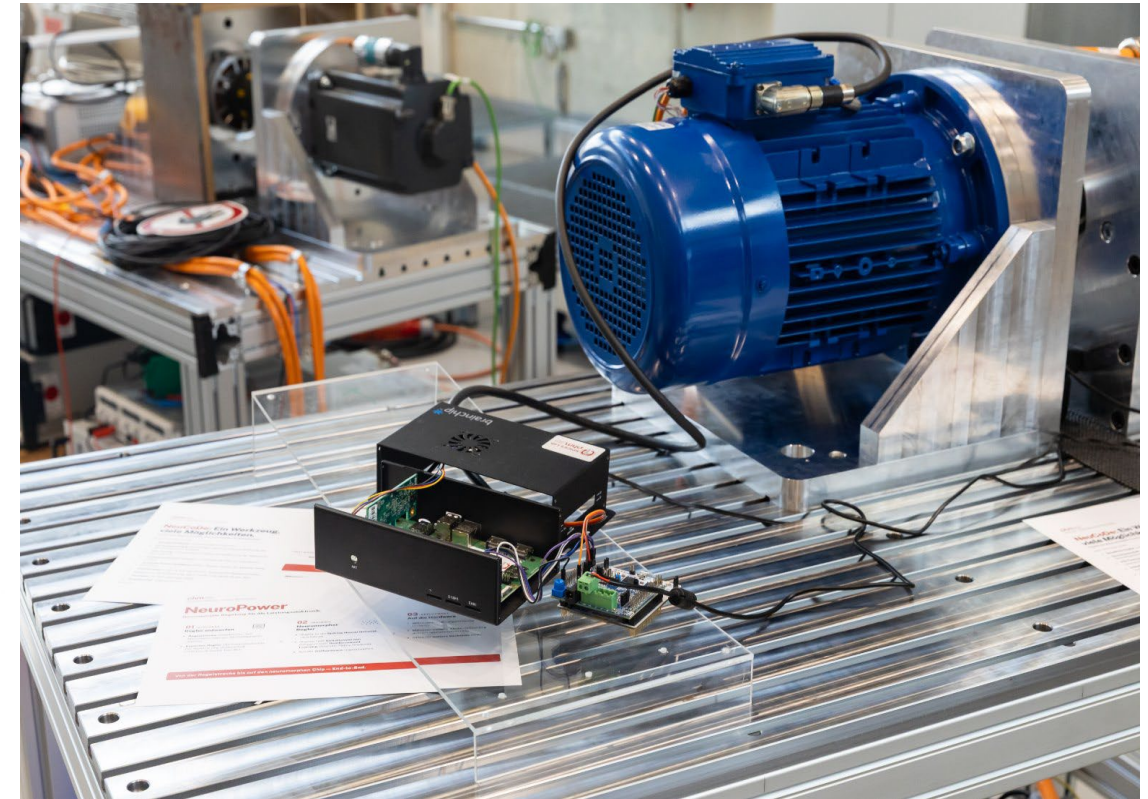
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Collaboration: Benedikt Fischer, SPICES Lab, OHM

gimbal (FOIPDT-trained, dense), snn / staircase: sim twin vs hardware



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Neuromorphic Feedback Control for
Power Electronics Systems
Success stories

Applications

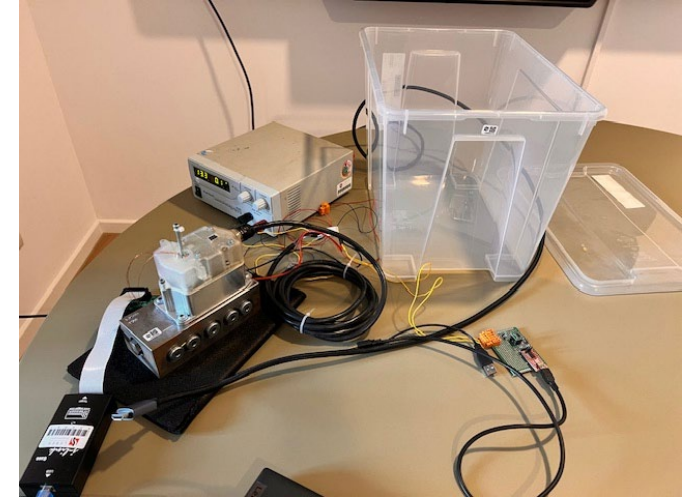
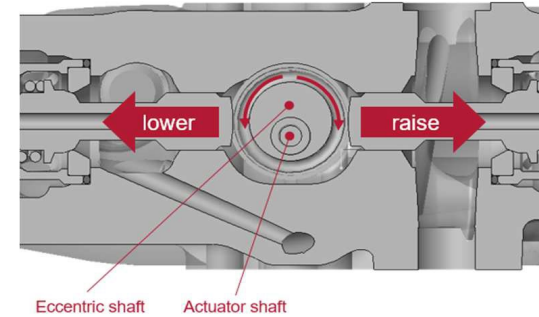
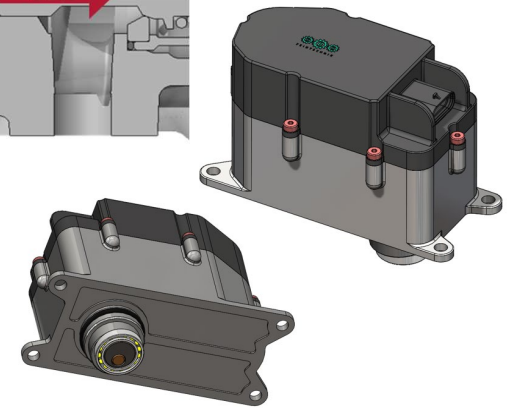
Actuator control for operating a hydraulic valve unit



Roadmap

Controller replication

ANN/
SNN



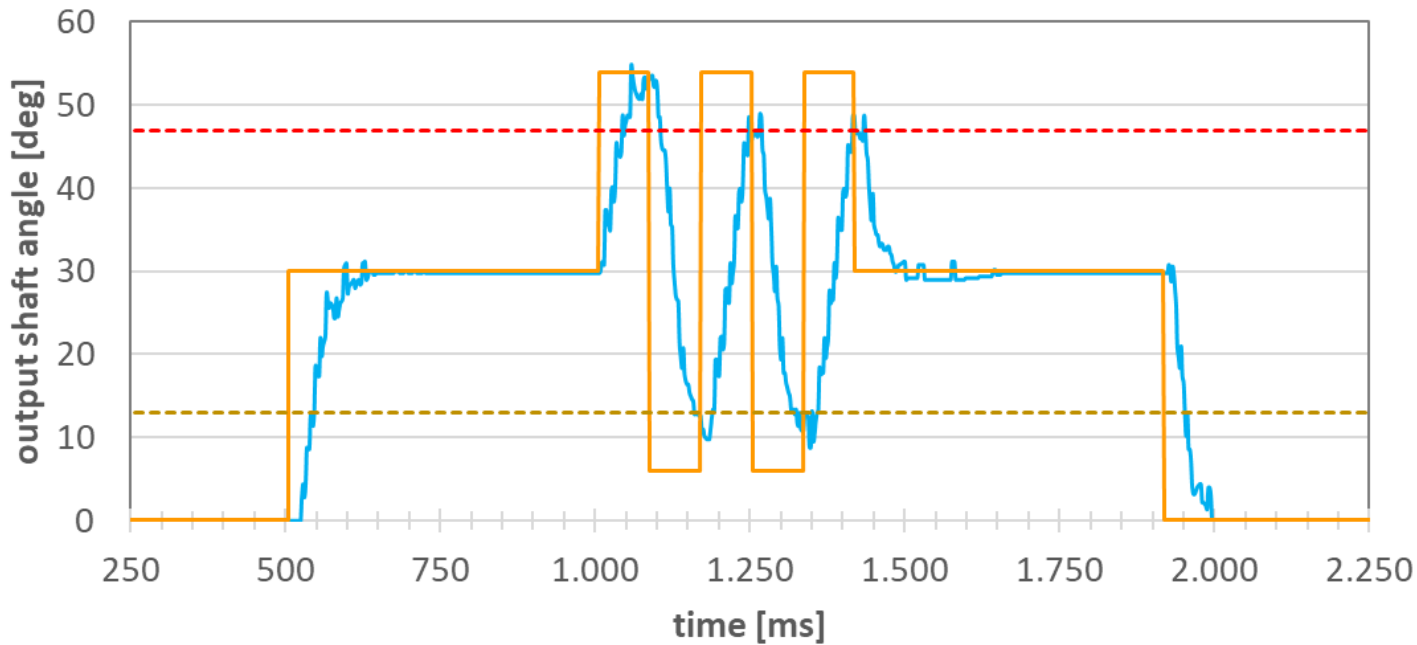
BURGER
ENGINEERING

Applications

Actuator control for operating a hydraulic valve unit

- Control range from -60° to $+60^{\circ}$
- The positioning time must be between 10% and 90% in <110 ms
- 3° within 30 ms at the latest
- The coupling play is learnt on switch-on
- The response time is relevant
- Test at 30° and 0°

frequency response $30^{\circ} \pm 24^{\circ}$ 6 Hz, 92°C , 9V



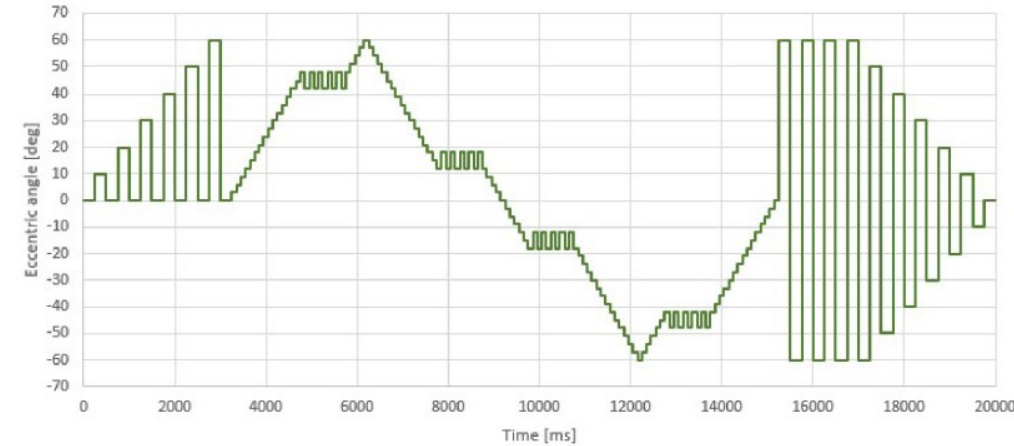
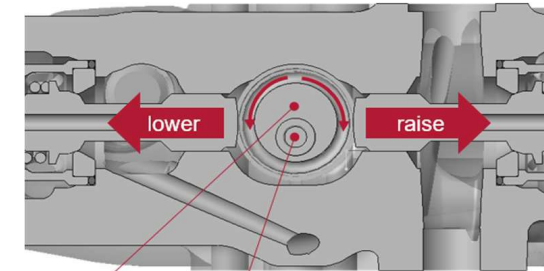
— response value — target value - - - upper limit - - - lower limit

Roadmap

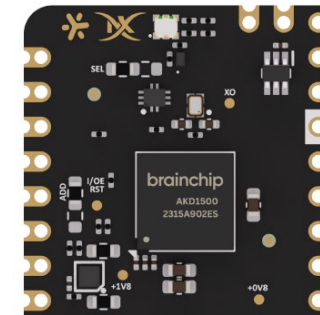
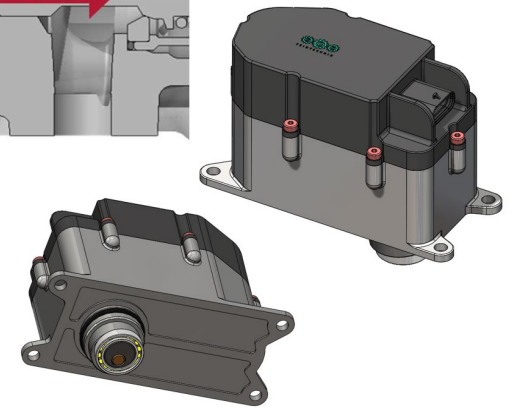
Controller replication

ANN/
SNN

Duty Cycle 1



Eccentric shaft Actuator shaft



BURGER
ENGINEERING

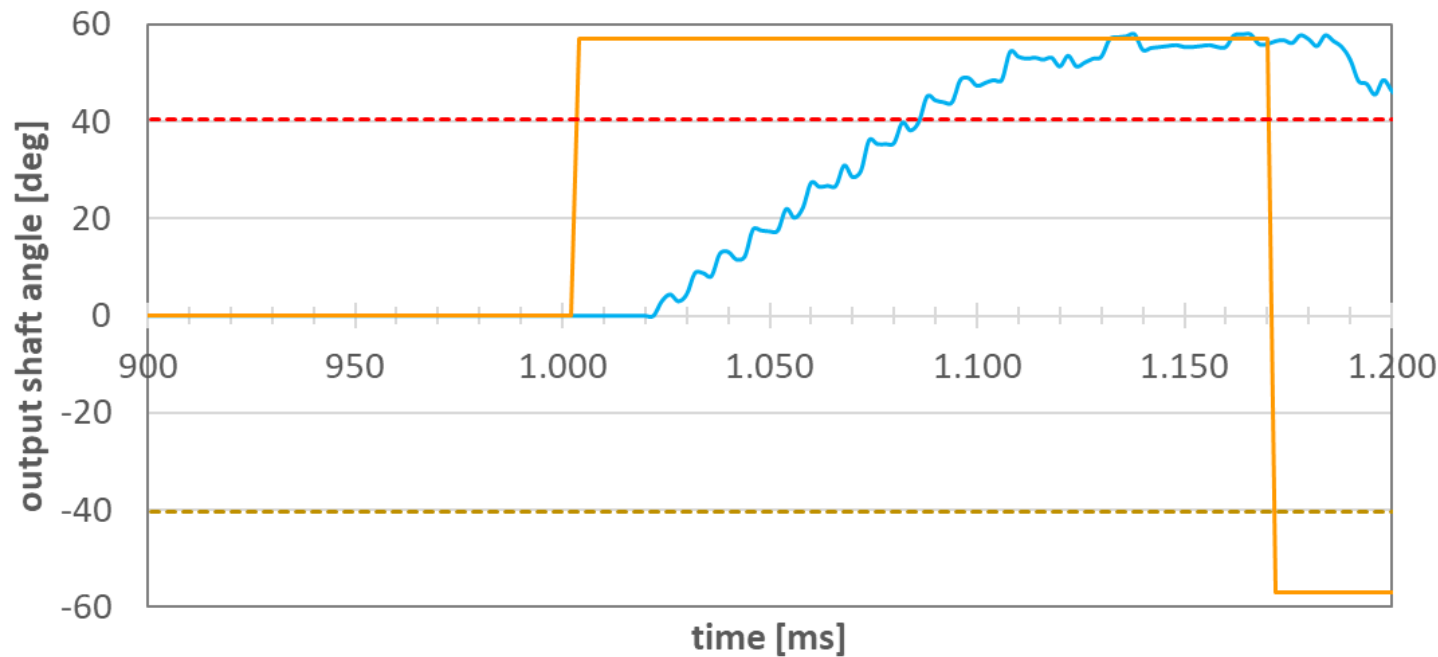
Collaboration: Leon Angele, Stefan Betzold, Burger Engineering

Applications

Actuator control for operating a hydraulic valve unit

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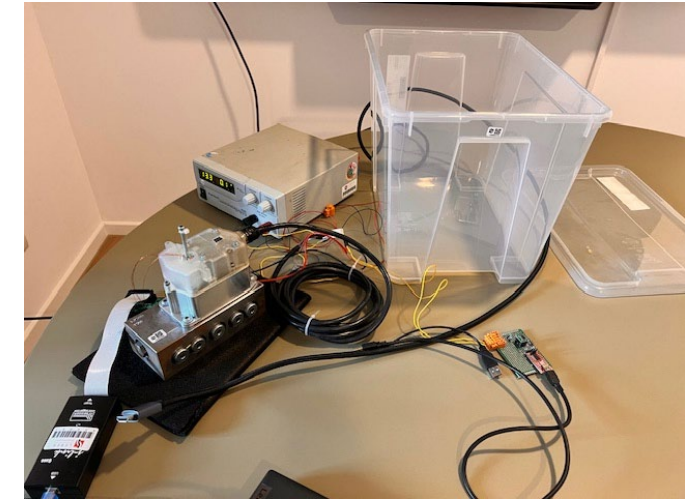
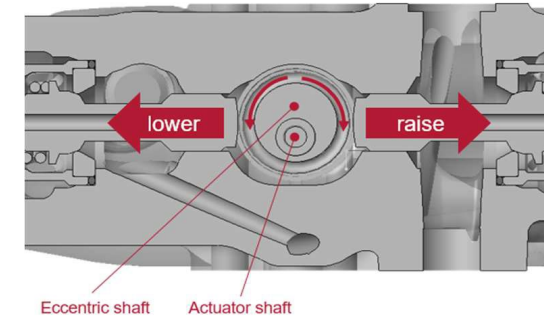
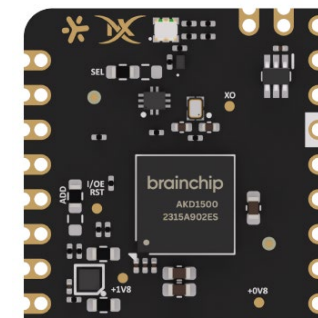
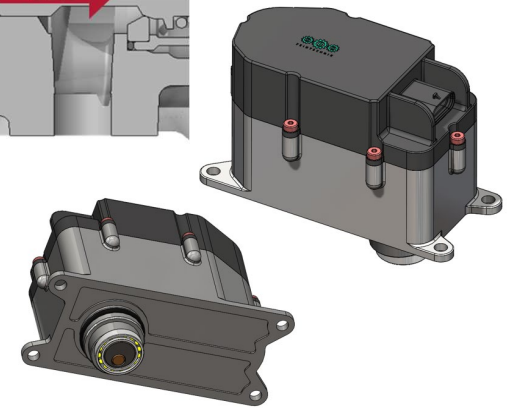
frequency response $0^{\circ} \pm 57^{\circ}$ 3 Hz, 92°C , 9V



— response value — target value - - - upper limit - - - lower limit

Roadmap

Controller replication



BURGER
ENGINEERING

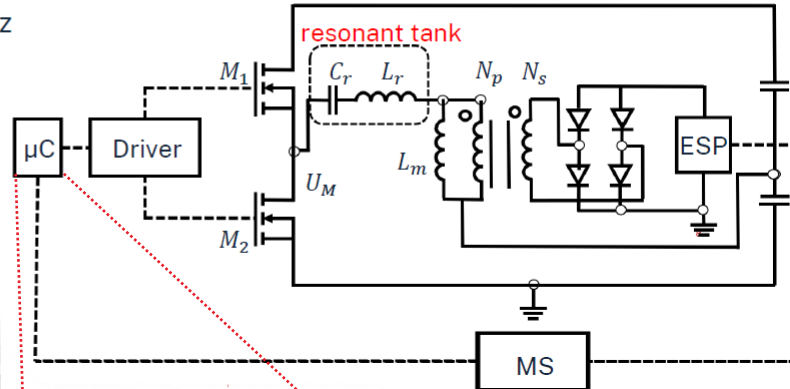
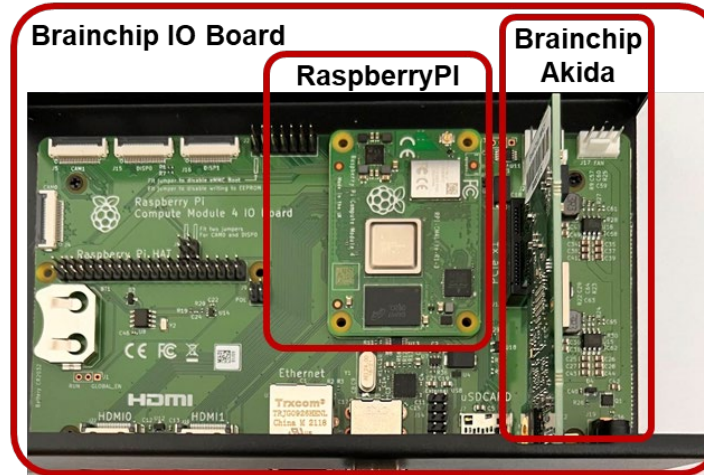
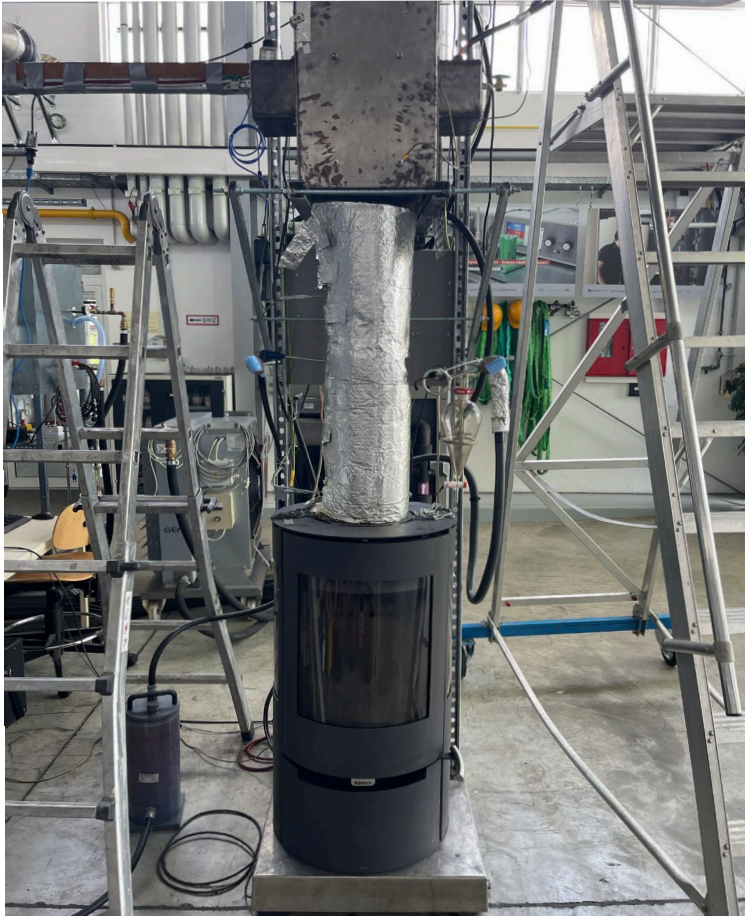
Collaboration: Leon Angele, Stefan Betzold, Burger Engineering

Applications

Regulation of a High-Voltage Power Supply for an Electrostatic Precipitator

Wide operating range, smooth control authority, and high efficiency

- Input voltage: 325V
- Output voltage (negative): 25kV – 35kV
- Switching frequency: 70 – 110kHz
- Resonant frequency: 100kHz



Roadmap

Controller replication



Applications

Regulation of a High-Voltage Power Supply for an Electrostatic Precipitator

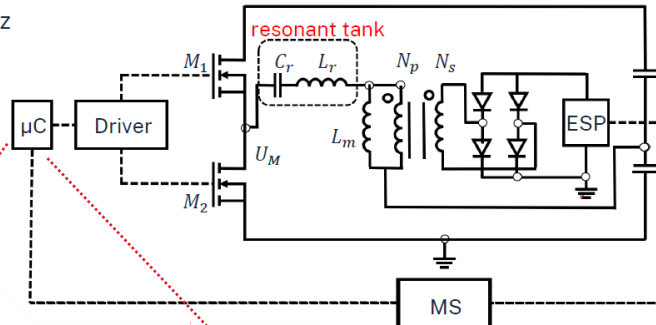
ANN/
SNN

Roadmap

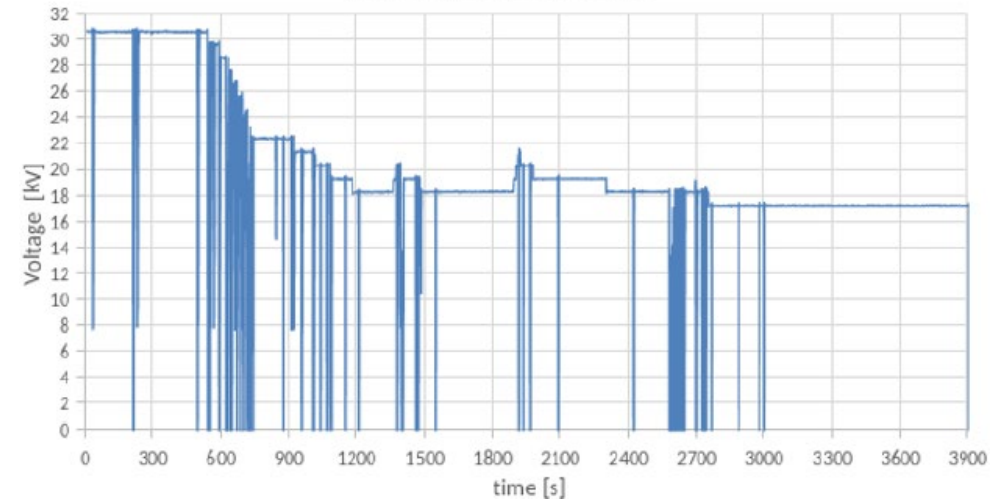
Controller replication

Wide operating range, smooth control authority, and high efficiency

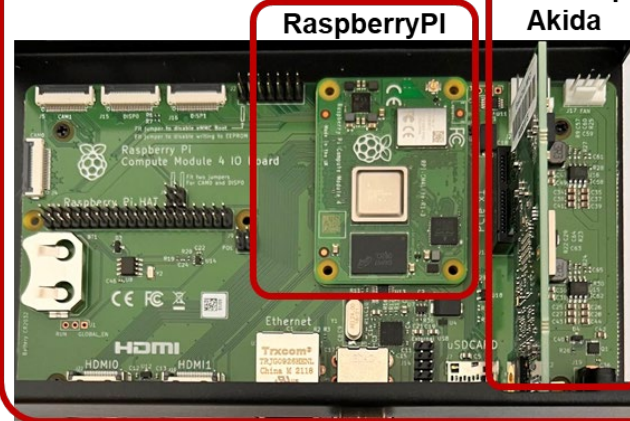
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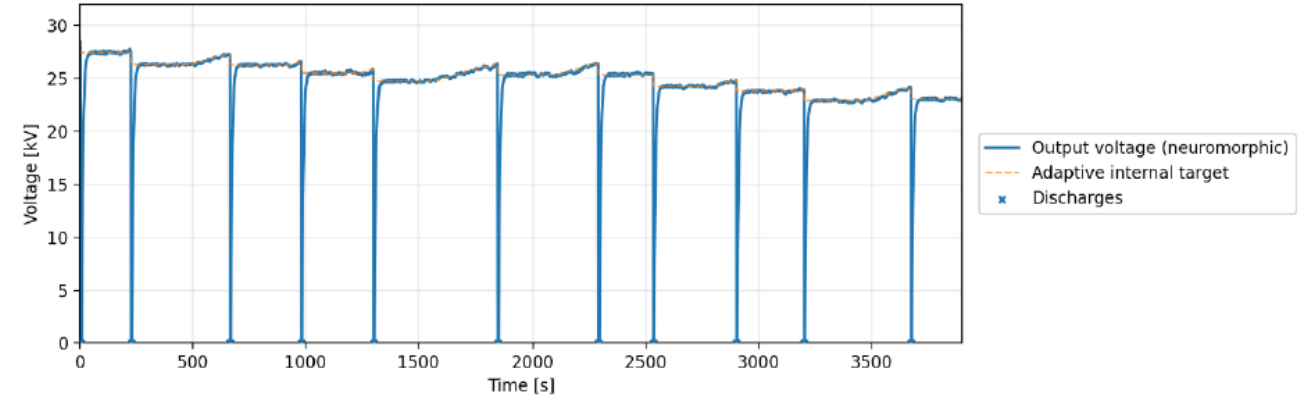
Voltage Prec1 OekoSolve



Brainchip IO Board

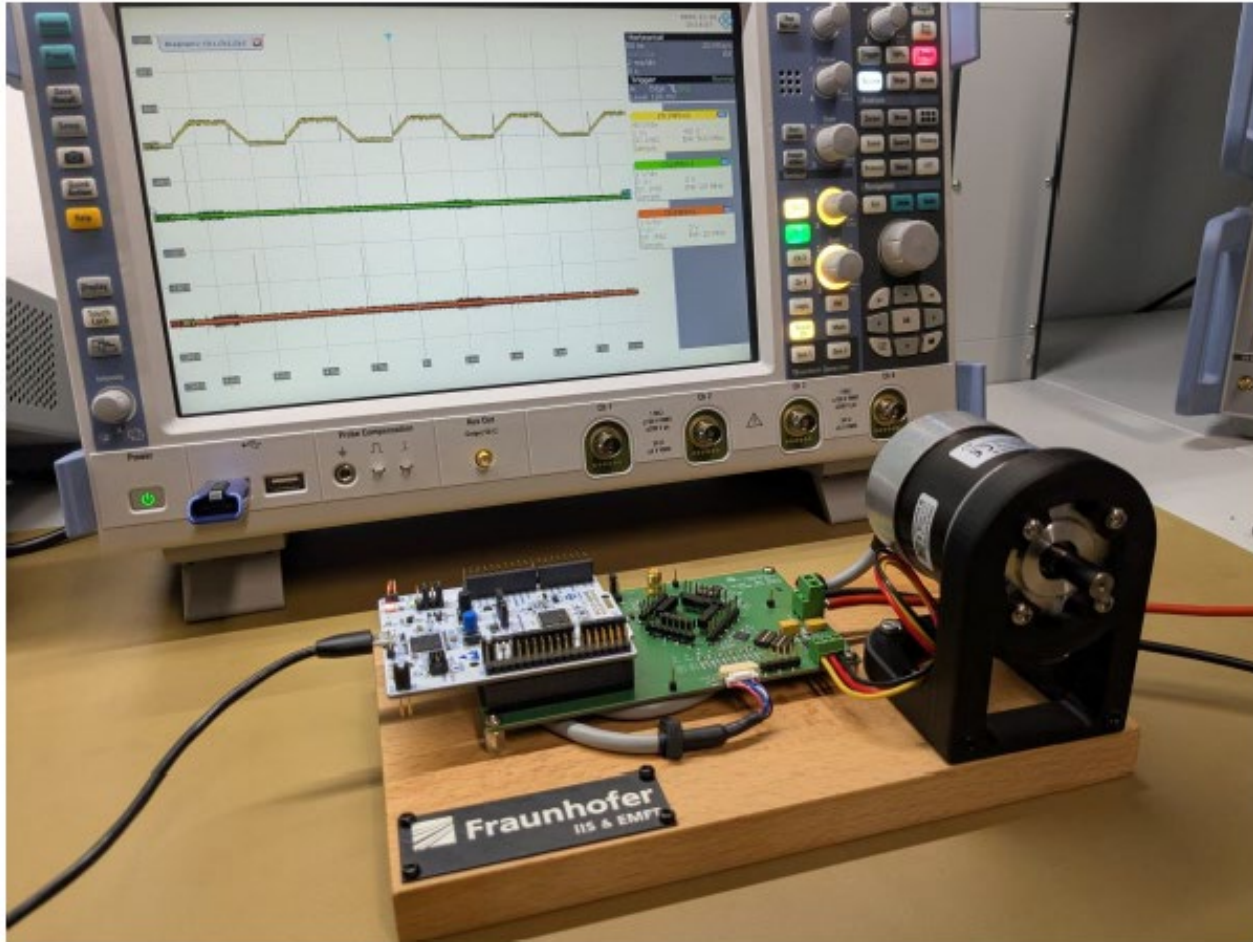
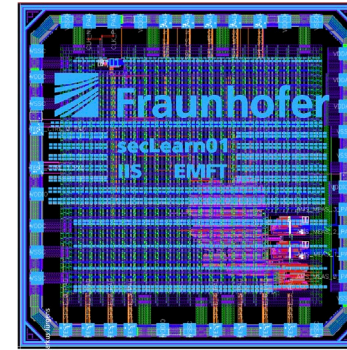


Neuromorphic Voltage Control - Adaptive Raise, Target Reduction on Discharge, Fast Recovery



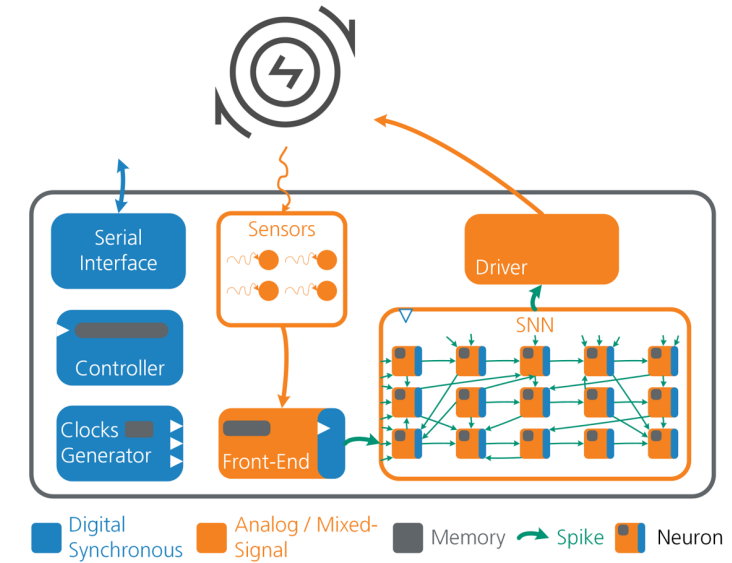
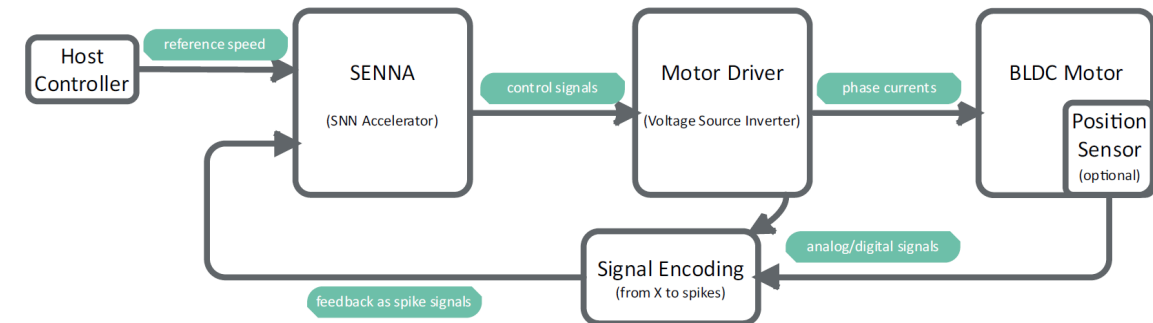
Applications

Sensorless BLDC Field-Oriented-Control



Roadmap

Standalone neuronal controller



- Fraunhofer **SENNA Chip**: mixed-signal circuit-switched field-programmable accelerator for SNNs
- Reference design in 22 nm GF FDSOI
 - 1024 neurons and 25.600 synapses $\triangleq$ 10 mm²
 - Minimal Response Time: 20 ns, Energy efficiency: 500 fJ/SOP

With funding from the:



Federal Ministry
of Research, Technology
and Space

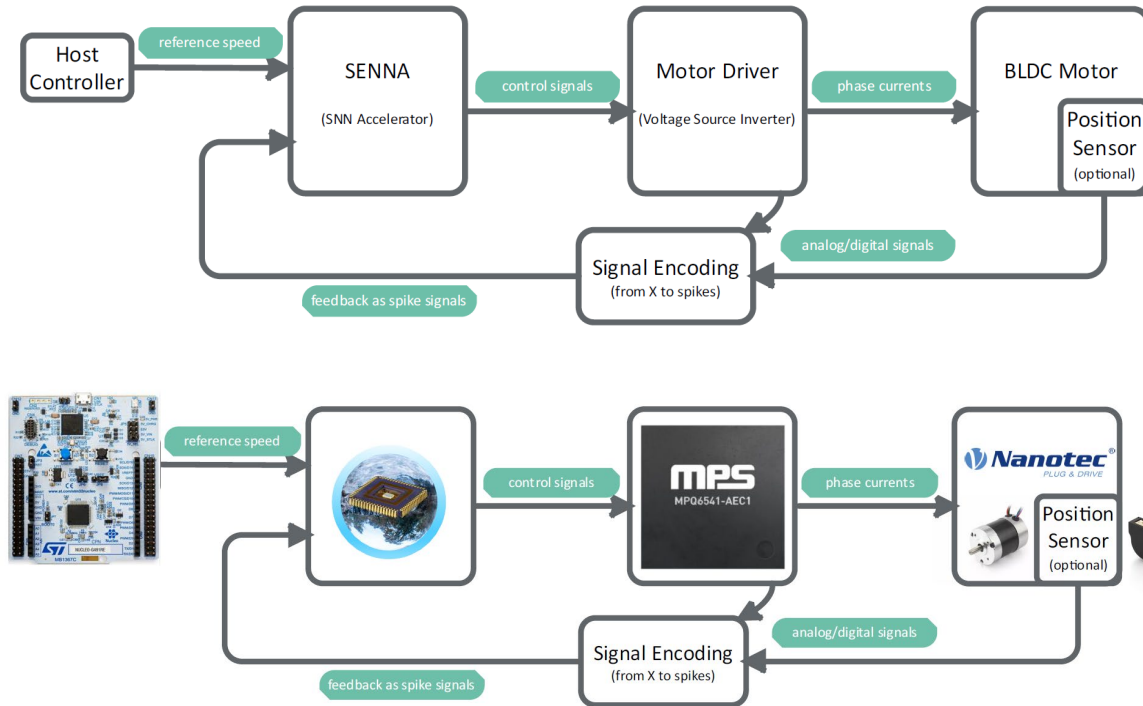
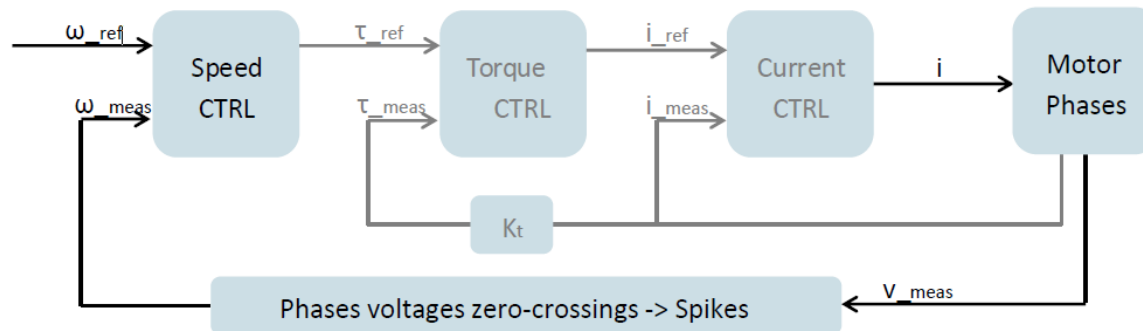
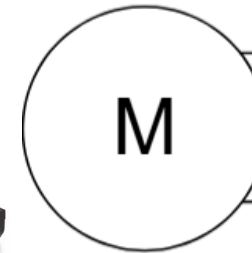
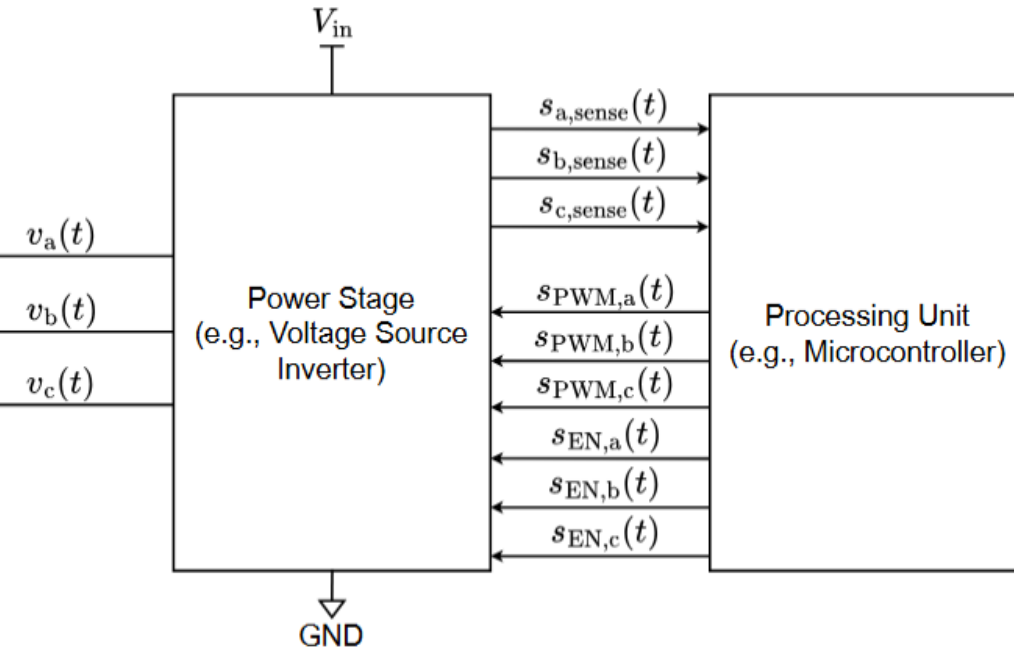
Applications

Sensorless BLDC Field-Oriented-Control



Roadmap

Standalone neuronal controller



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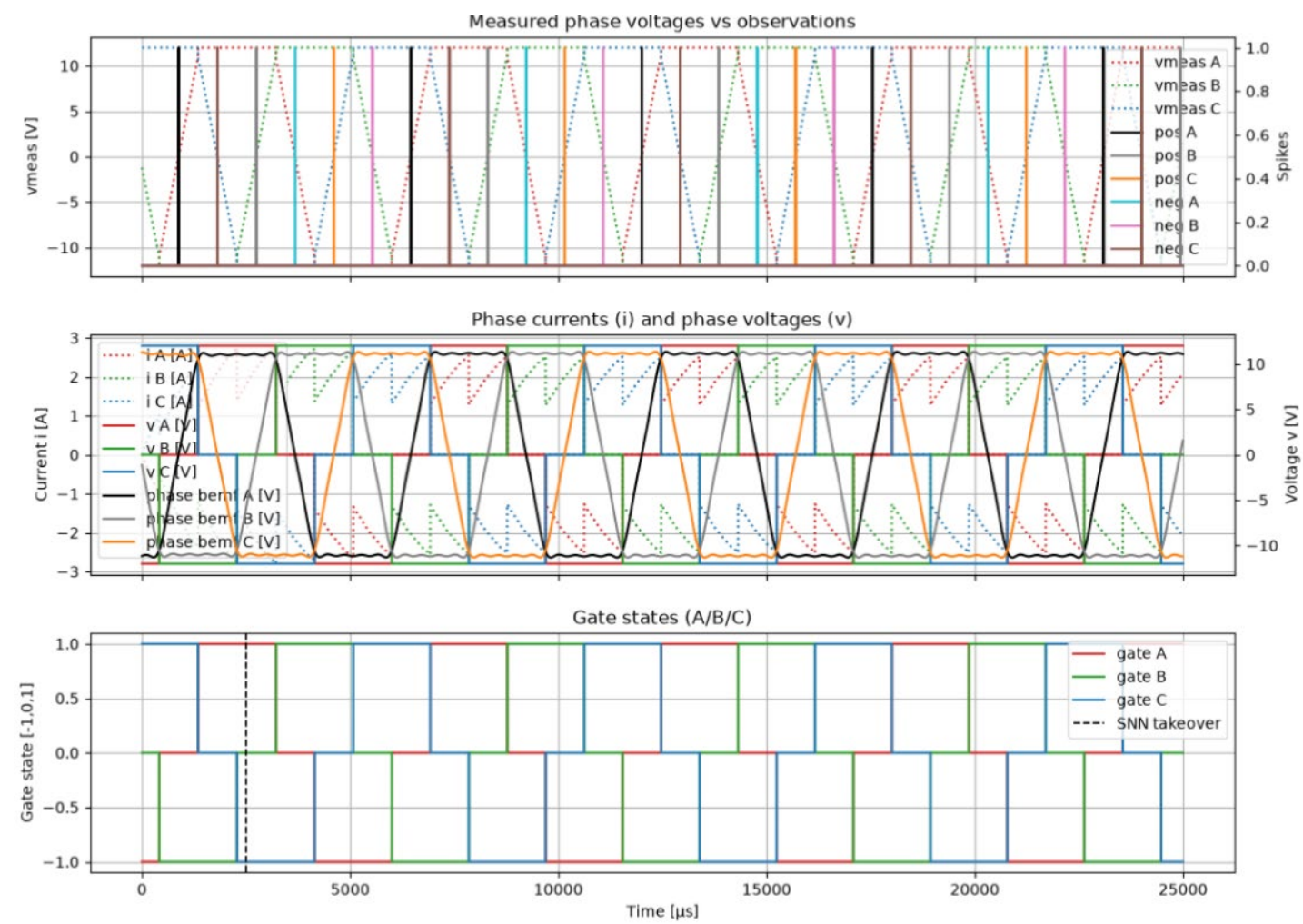
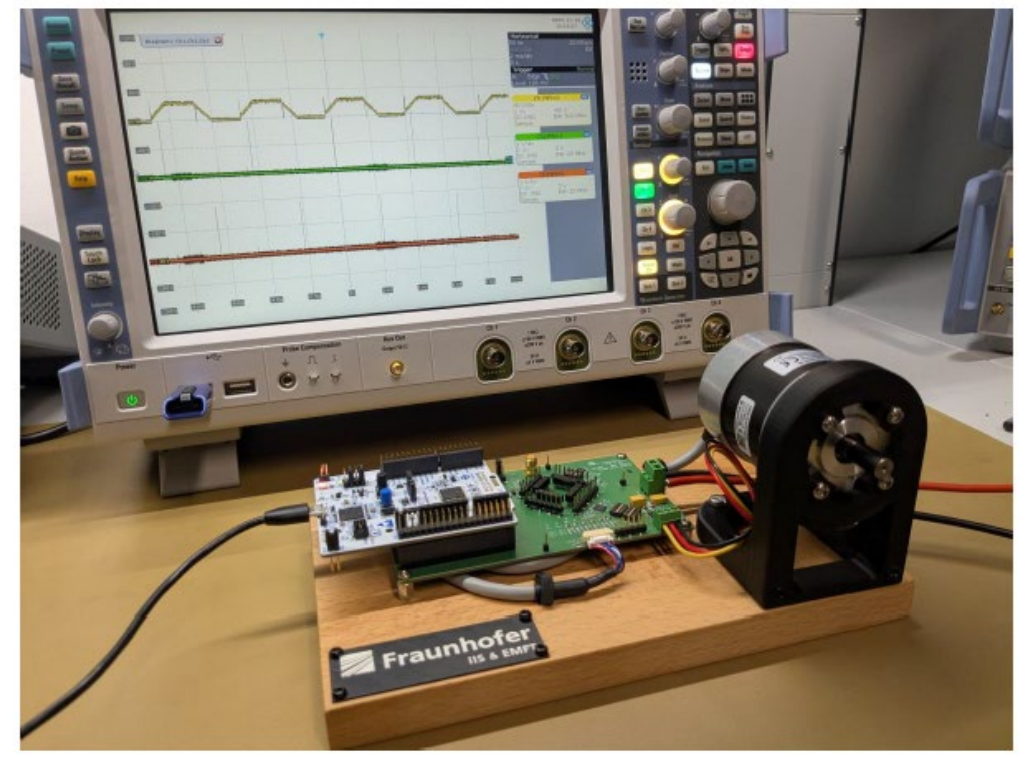
Applications

Sensorless BLDC Field-Oriented-Control



Roadmap

Standalone neuronal controller

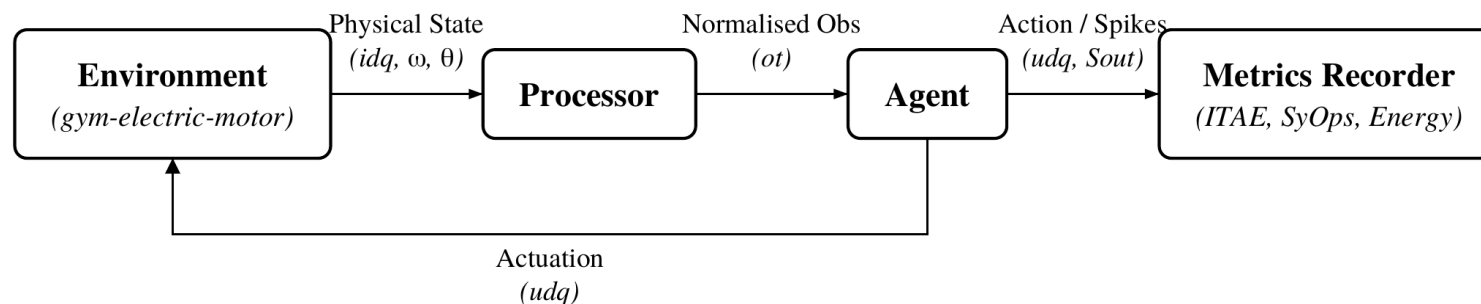
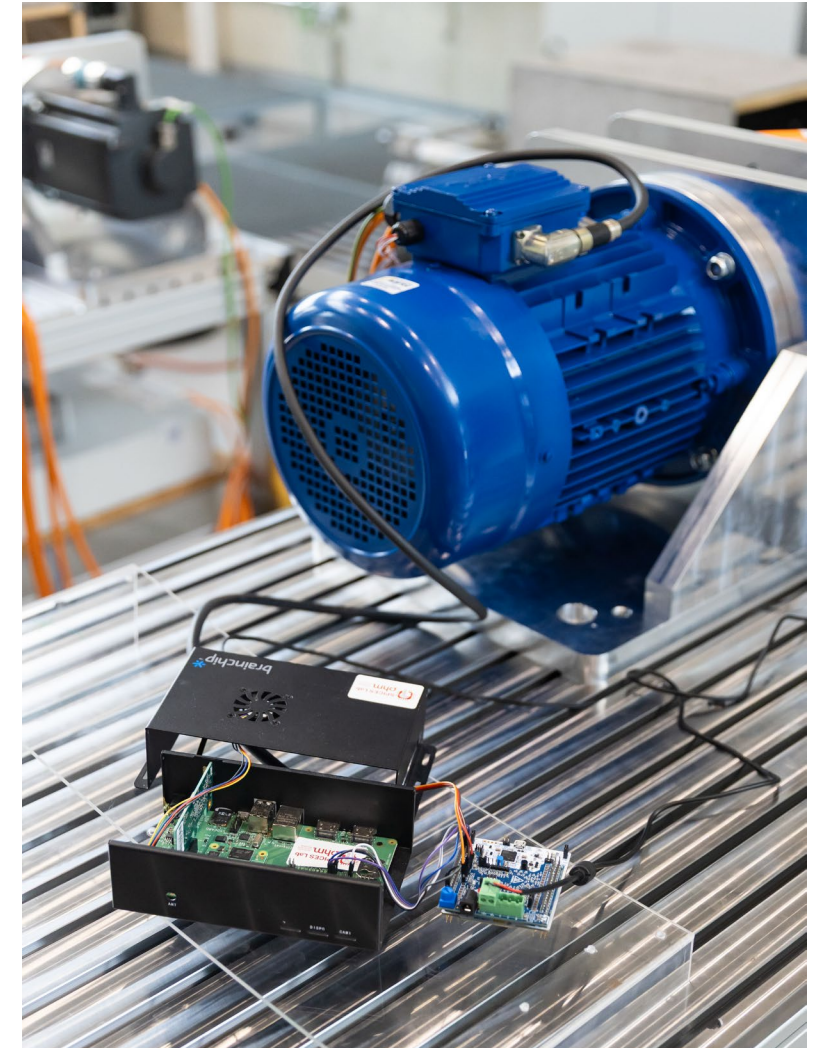


With funding from the:

EMABARK

Evaluates control quality and neuromorphic deployment

- Running a physics-based electric motor simulation at 10 kHz
- Enforcing synchronous, causal execution
- Creating a standardized interface
- Measuring timing and dynamic control behavior
- Testing both software and neuromorphic hardware



Collaboration: Younes Bouhadjar, Fraunhofer IIS, Jonas Reif, OHM

Acknowledgments:

This work was funded by the STAEDTLER-Stiftung Grant No. WW/ar 09/25 (Project NeuroPower) and partially by the Fraunhofer Research Programs Grant No. Attract 40-11894

Six canonical motor-control scenarios

The test bench spans transient response, tracking, steady state, and axis coupling

Table 1. Canonical Benchmark Scenarios.

ID Name	ω (rpm)	i_q^* (A)	Duration(s)
S1 Low-speed Step	500	$0 \rightarrow 2$	0.3
S2 Mid-speed Step	1500	$0 \rightarrow 2$	0.3
S3 High-speed Step	2500	$0 \rightarrow 2$	0.3
S4 Bidirectional Multi-step	1500	± 2 (4-st)	1.0
S5 Four-quadrant Trans.	1500	$+2 \rightarrow -2 \rightarrow 0$	0.9
S6 Field Weakening	2500	$0 \rightarrow 2$	0.6

Each scenario specifies

S1–S3: Torque-current step response at different motor speeds.

S4–S5: Dynamic tracking, reversals, and steady-state consistency.

S6: d–q current coupling during high-speed field weakening.

PMSM, inverter, and mechanical load with a 10 kHz control step

Collaboration: Younes Bouhadjar, Fraunhofer IIS, Jonas Reif, OHM

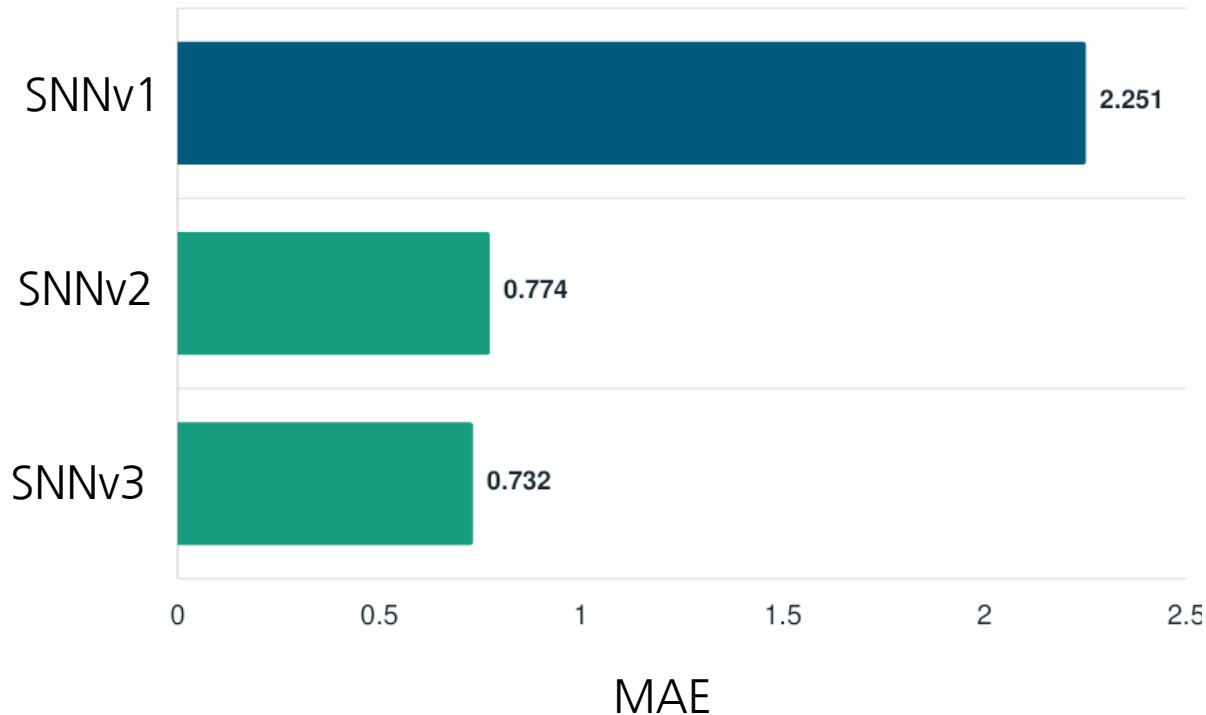
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Ground-truth calibration separates controller quality

Mean MAE across the six scenarios reproduces the expected SNN ranking

Mean across S1-S3



SNNv1: LIF-based network with hidden layers [128, 96, 64]; trained using open-loop imitation learning.

SNNv2: same network as above. Trained using scheduled sampling and BPTT through PMSM voltage and current trajectories.

SNNv3: same network as above; predicts **incremental voltage changes** instead of absolute voltages; uses **two-phase hybrid training** with imitation learning and closed-loop BPTT

SNNv3 ranks first at 0.732 A mean MAE, closely followed by SNNv2 at 0.774 A. SNNv1 performs the worst.

Collaboration: Younes Bouhadjar, Fraunhofer IIS, Jonas Reif, OHM

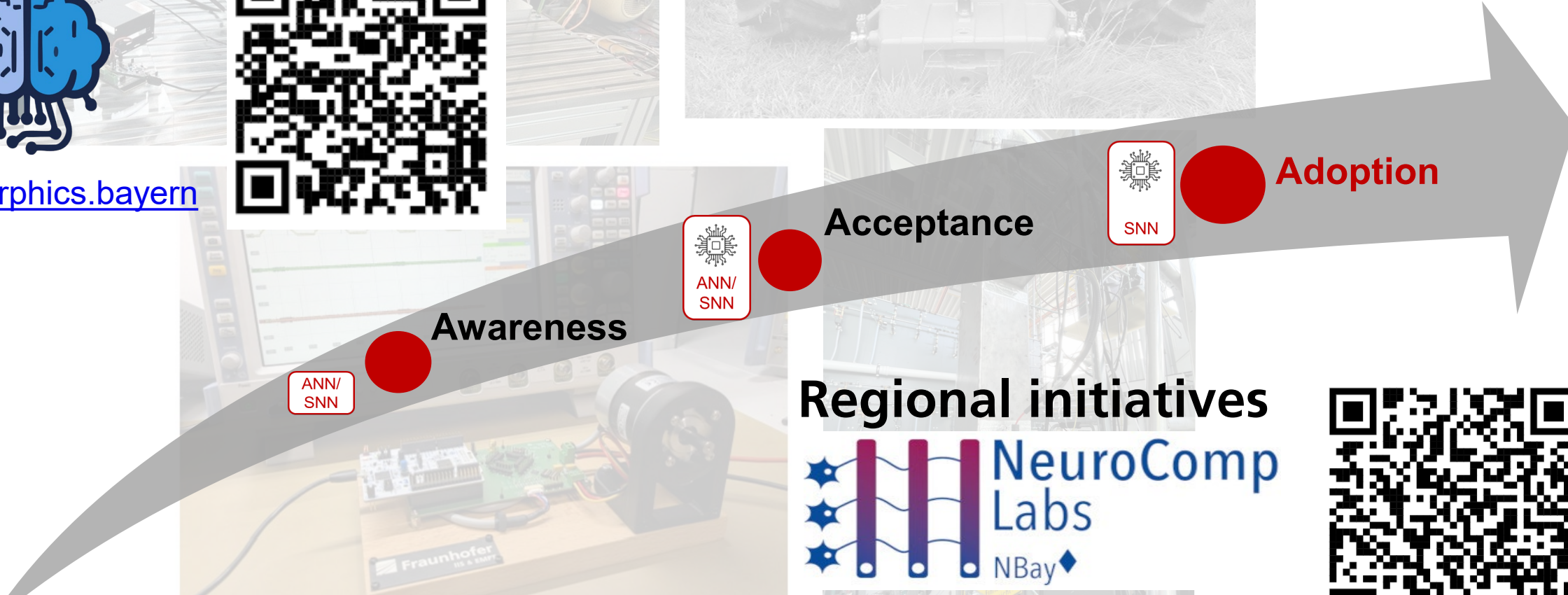
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Local initiatives



neuromorphics.bayern



Regional initiatives



The team



Maximilian
Werzinger



Igor
Bodyagin



Ana Beatriz
Lordeiro Barbosa



Bendikt
Fischer



Lena
Neumeier



Daniel
Pommer



Max
Fuhrmann



Cristian
Axenie



Andreas
Stoll



Younes
Bouhadjar



Alexander
Jaschke



Priyanka
Balakrishna
Hejmadi

SPICES Lab

Sensorimotor Processing Intelligence and Control in Edge Systems

NCS Lab

Neuromorphic Computing Solutions