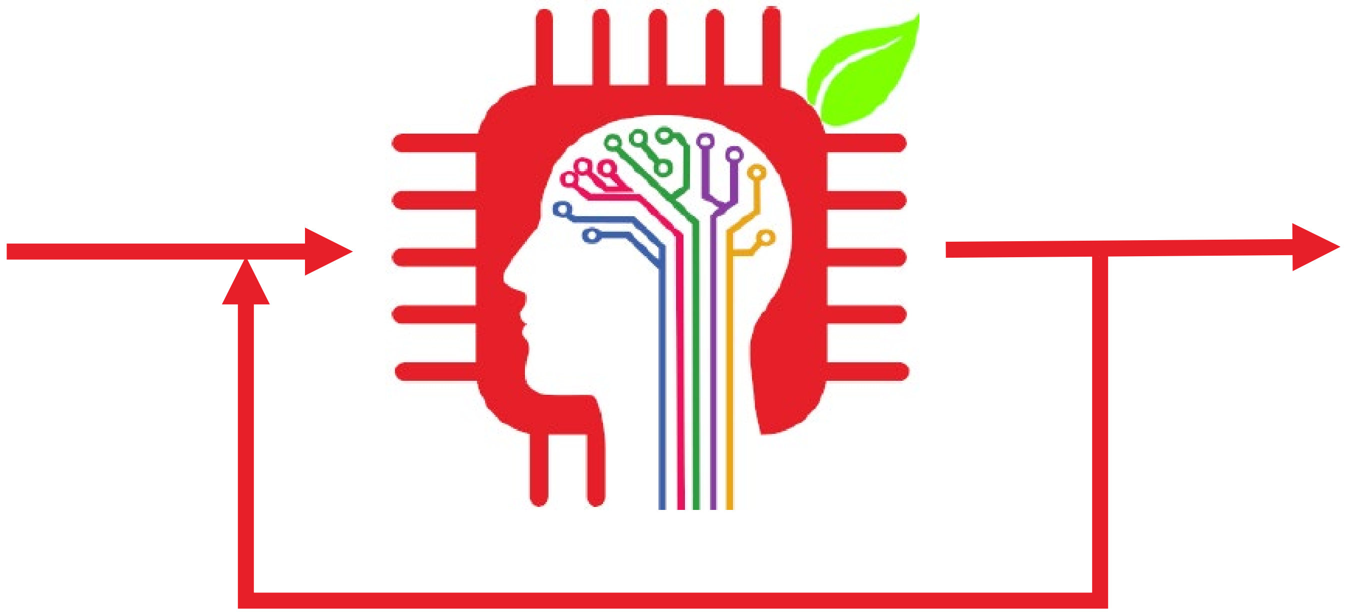


Neural Networks for Low-Latency, High-Reliability Control in Power Conversion Systems

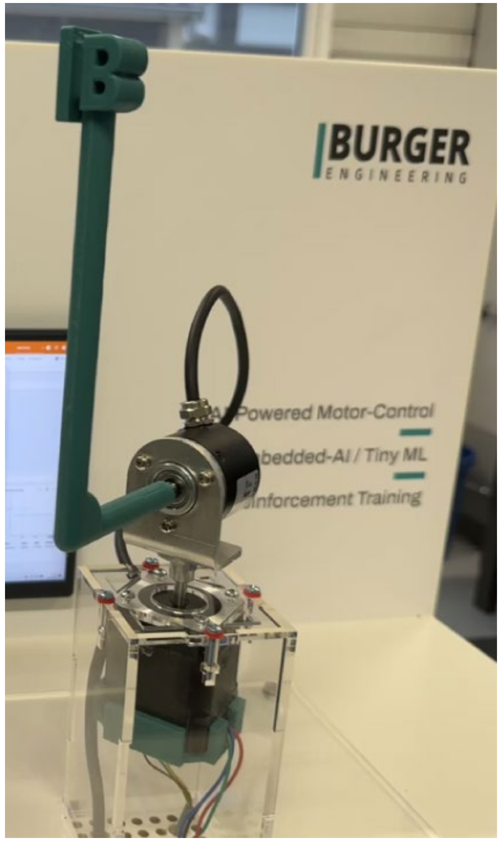
The EdgeAI Approach...is WIP

Prof. Dr. Cristian Axenie

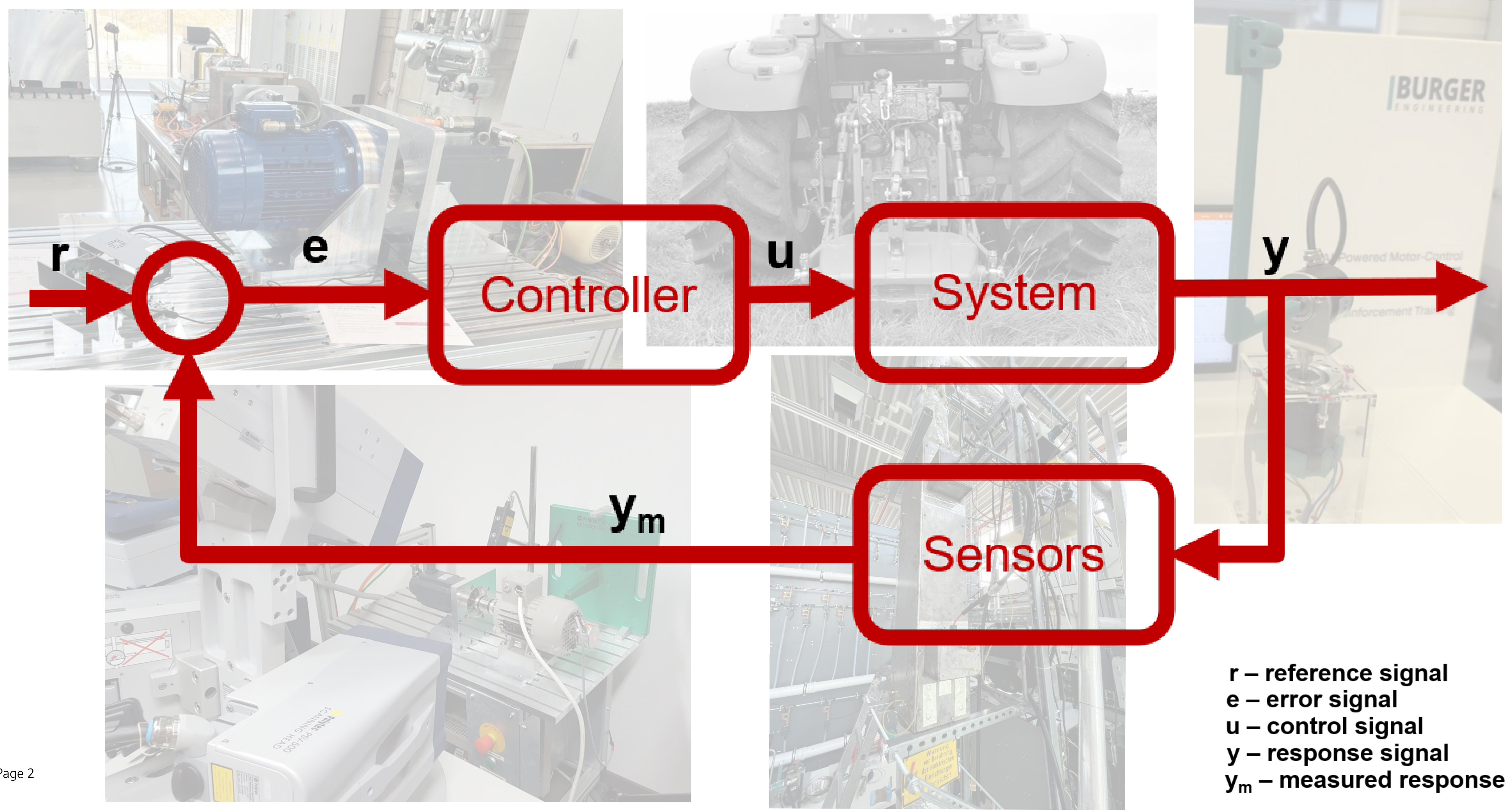
ohm Technische Hochschule Nürnberg

Fraunhofer IIS

Power conversion systems

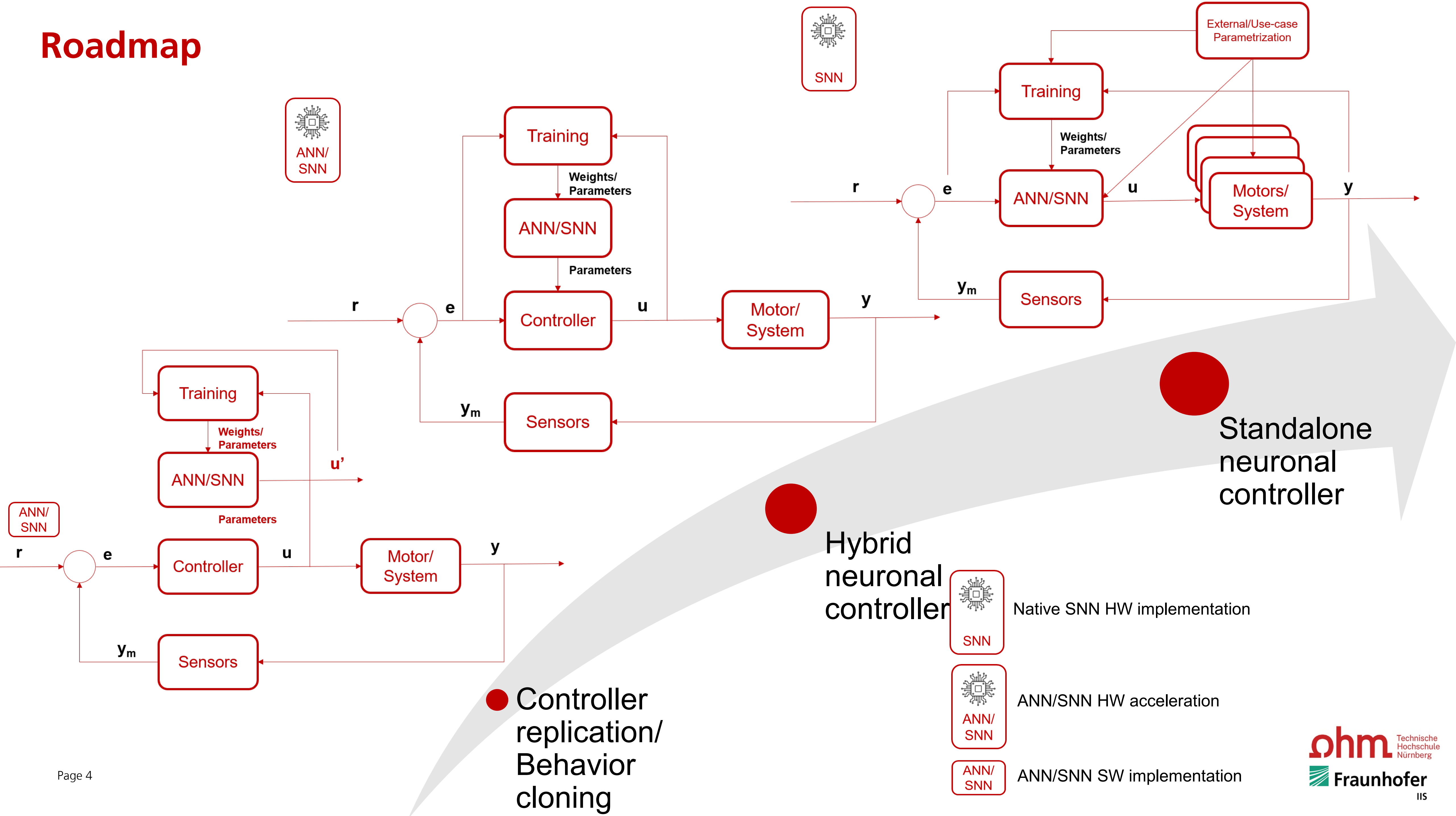


Control of power conversion systems



r – reference signal
e – error signal
u – control signal
y – response signal
y_m – measured response

Roadmap



Technische Hochschule Nürnberg
Fraunhofer IIS

NeuCoDe

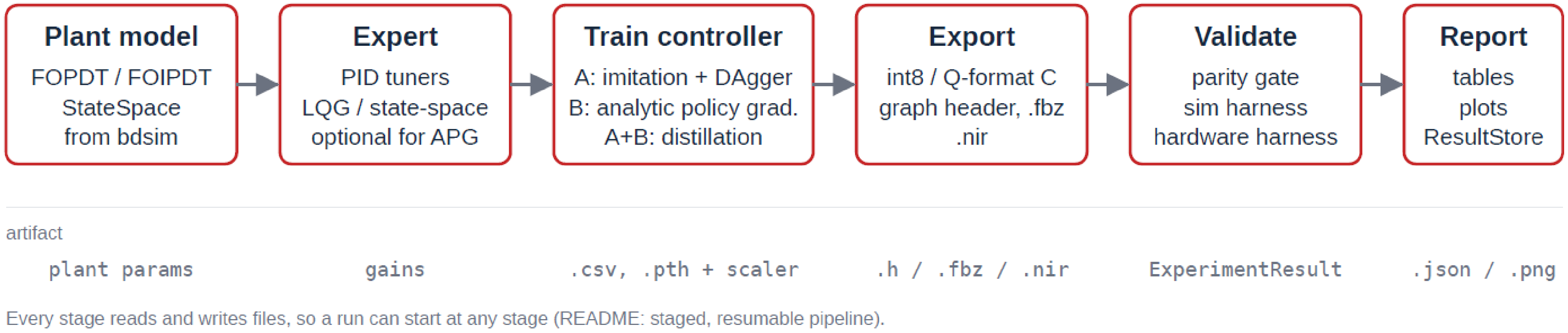
NEURAL CONTROL DEPLOYMENT TOOLKIT

Characterise > Generate > Train > Export > Validate > Deploy

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

Collaboration: Benedikt Fischer, SPICES Lab, OHM

Capability	NeuCoDE	NeuroBench	Mathematica	MATLAB
Closed-loop causal execution	✓	—	✓	✓
Physics simulation	✓	—	—	✓
Controller deployment	✓	Partial	—	Partial
Controller tuning	✓	—	Partial	✓
Control performance metrics	✓	Partial	✓	✓
Deployment metrics	✓	Partial	—	Partial
Open-source accessibility	✓	✓	—	—



- 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.

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Fragmented: control design, training, and embedded deployment are disconnected

Full end-to-end workflow from design to deployment

Bridges simulation and physical validation via shared metrics and telemetry

No reproducible workflow from simulation to embedded deployment

One **reproducible** pipeline

Embedded-ready export

Plant model
FOPDT / FOIPDT
StateSpace
from bdsim

→

Expert
PID tuners
LQG / state-space
optional for APG

→

Train controller
A: imitation + DAgger
B: analytic policy grad.
A+B: distillation

→

Export
int8 / Q-format C
graph header, .fbz
.nir

→

Validate
parity gate
sim harness
hardware harness

→

Report
tables
plots
ResultStore

artifact

Plant model	Expert	Train controller	Export	Validate	Report
`plant params`	`gains`	`.csv, .pth + scaler`	`.h / .fbz / .nir`	`ExperimentResult`	`.json / .png`

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.

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Characterise > Generate > Train > Export > Validate > Deploy

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TRAINED MODEL	EXPORTER	ARTIFACT	RUNS ON
GraphExportable policy `graph_spec() -> [GraphNode]` RLNativeSNNPolicy, catalog variants, compensator chain	**c_graph.emit_c_header** float32 weights, 10 node kinds	`model_graph.h`	**MCU graph runtime** firmware/graph_runtime/graph.c
	NIRExporter Input-Linear-LIF-Affine-Output	`model.nir`	**NIR backends** Lava-DL, Sinabs, Rockpool, ...
HybridControlSNN / PopulationControlSNN snnTorch, AkidaExportable	**SNNExporter** branch-aware Q-format	`snn_model.h + scaler`	**MCU, SNN mode** firmware/controller/snn
	AKD1000Exporter fuse, fine-tune, 4-bit, cnn2snn	`model.fbz + scaler`	**Akida AKD1000** host + MCU external mode
MLP (ANN) DefaultMLPArchitecture	**ANNExporter** int8 weights, int32 bias	`ann_model.h + scaler`	**MCU, ANN mode** firmware/controller/ann

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NeuCoDe

NEURAL CONTROL DEPLOYMENT TOOLKIT

Characterise > Generate > Train > Export > Validate > Deploy

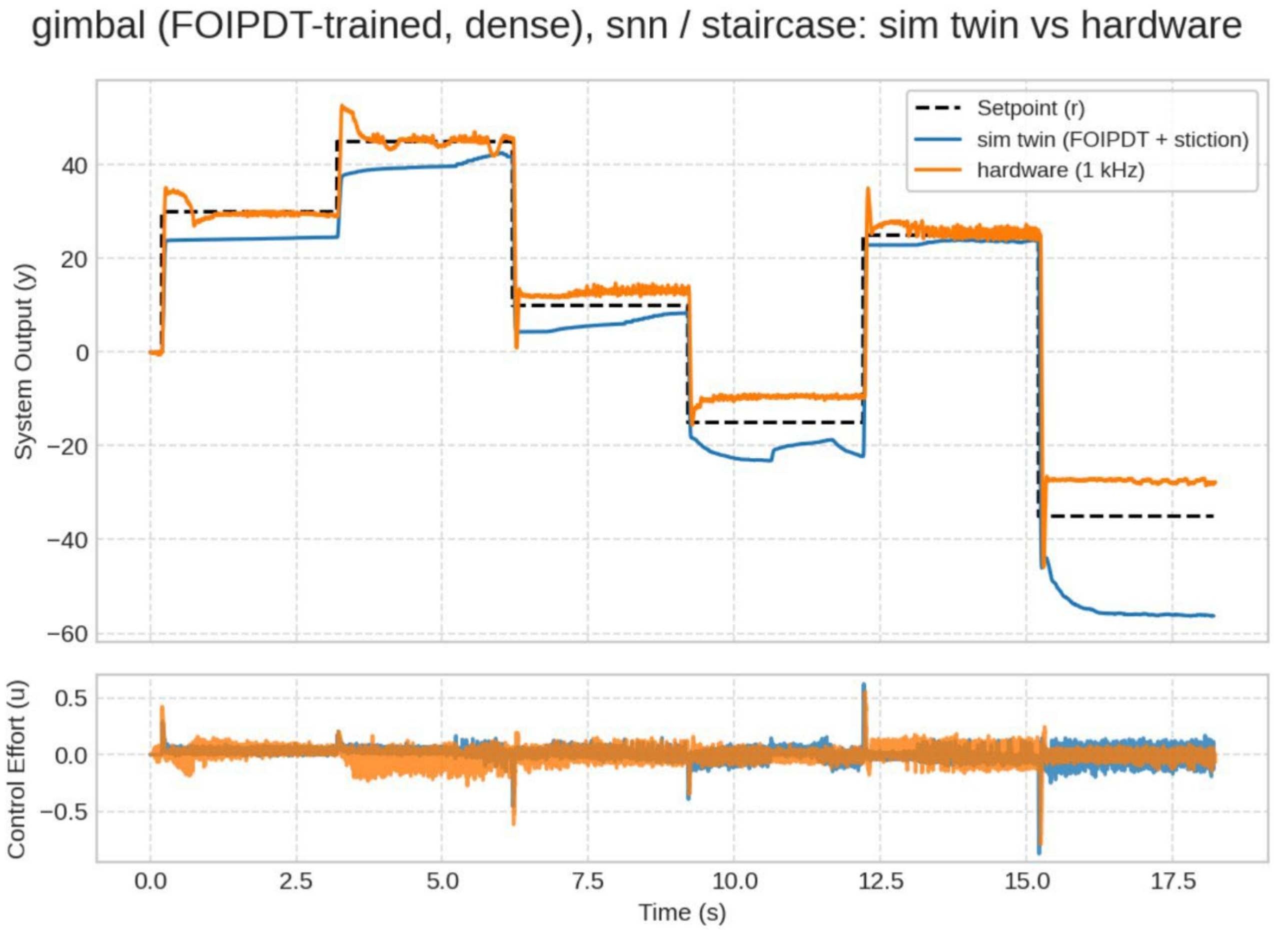
Toolkit for neural and neuromorphic control design and deployment on resource-constrained devices

SNN

ANN/ SNN

ANN/ SNN

Collaboration: Benedikt Fischer, SPICES Lab, OHM



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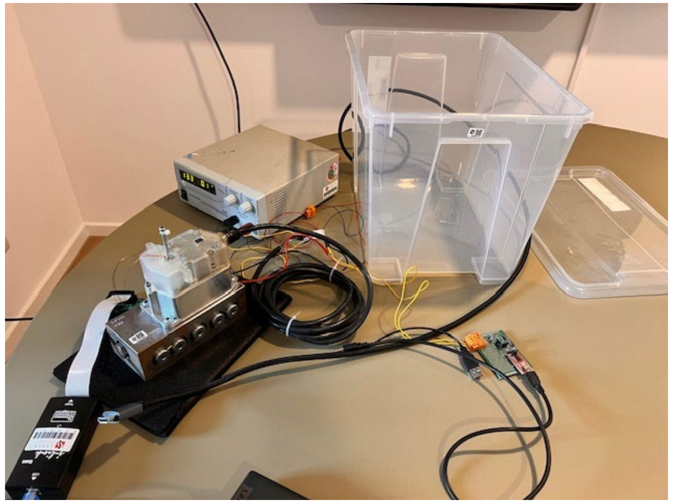
Applications

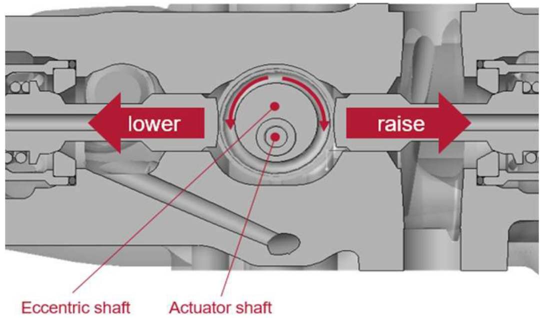
Actuator control for operating a hydraulic valve unit

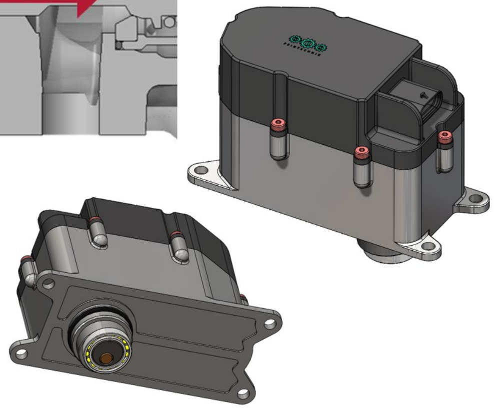
Roadmap

ANN/ SNN

Controller replication





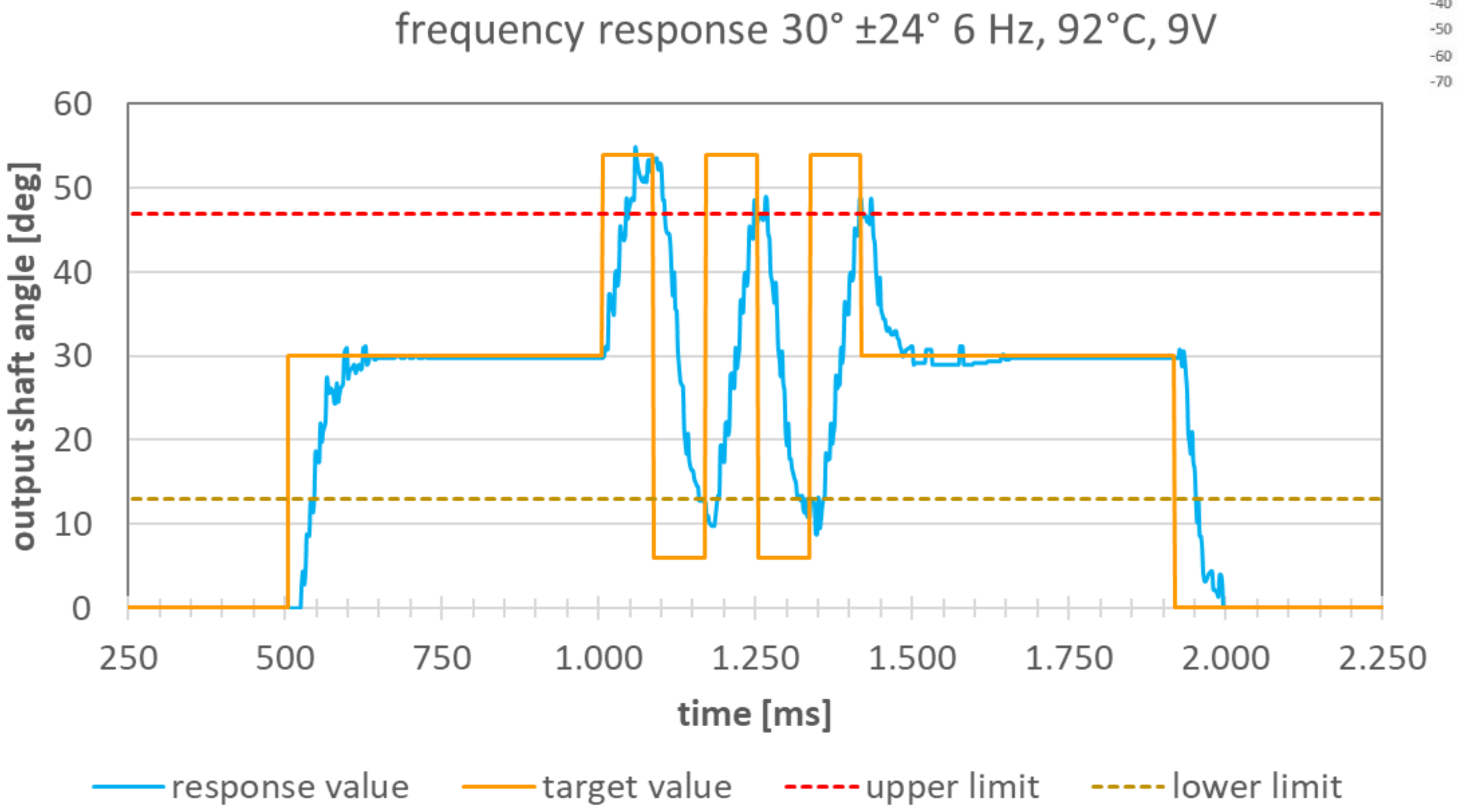


Collaboration: Leon Angele, Stefan Betzold, Burger Engineering

Applications

Actuator control for operating a hydraulic valve unit

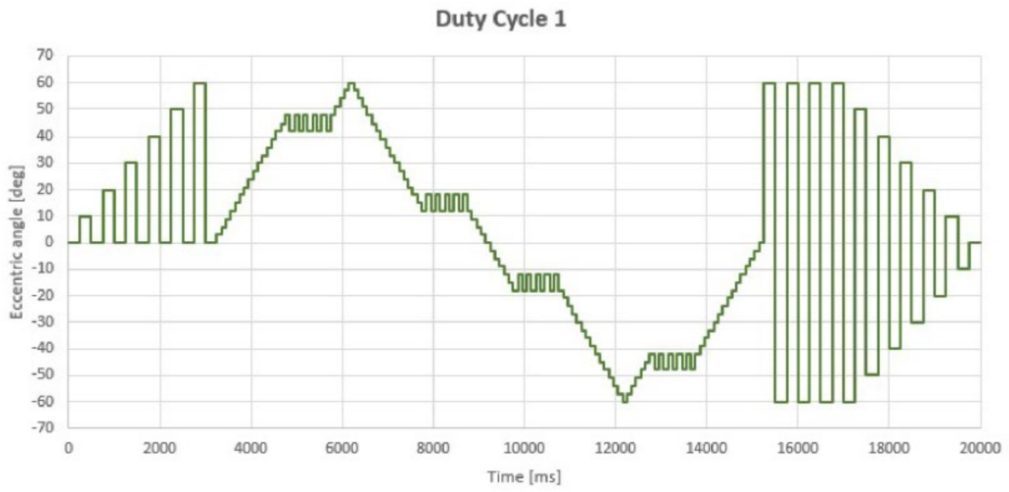
- Control range from -60° to +60°
- The positioning time must be between 10% and 90% in <110 ms
- 3° within 30 ms at the latest
- The coupling play is learnt on switch-on
- The response time is relevant
- Test at 30° and 0°

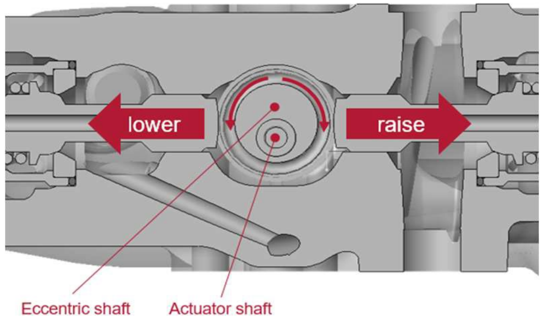


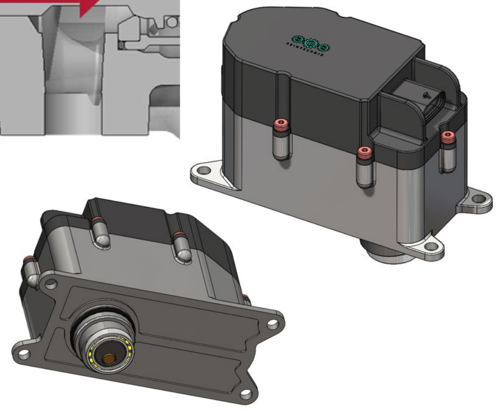
Roadmap

ANN/ SNN

Controller replication







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BURGER ENGINEERING

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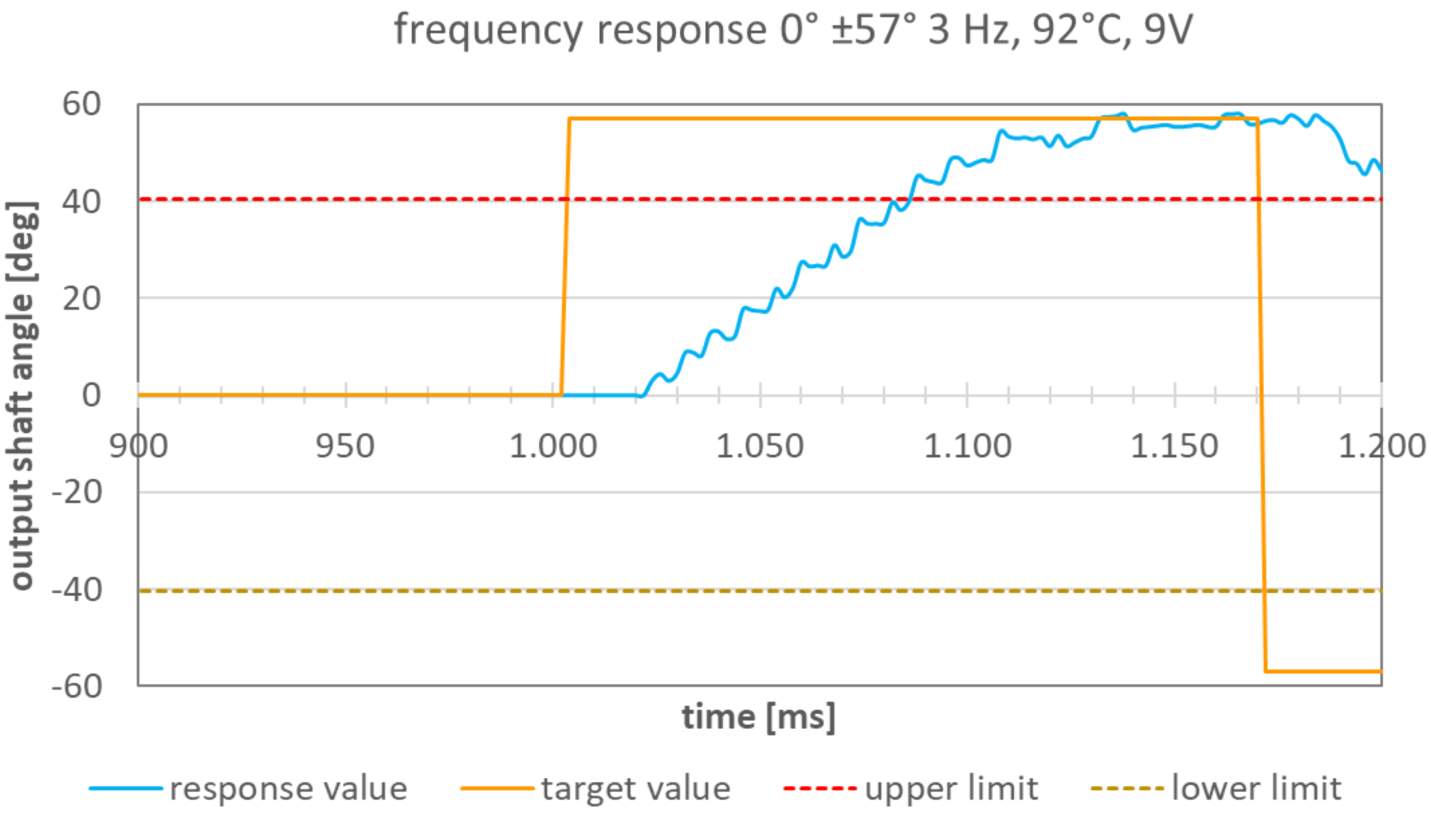
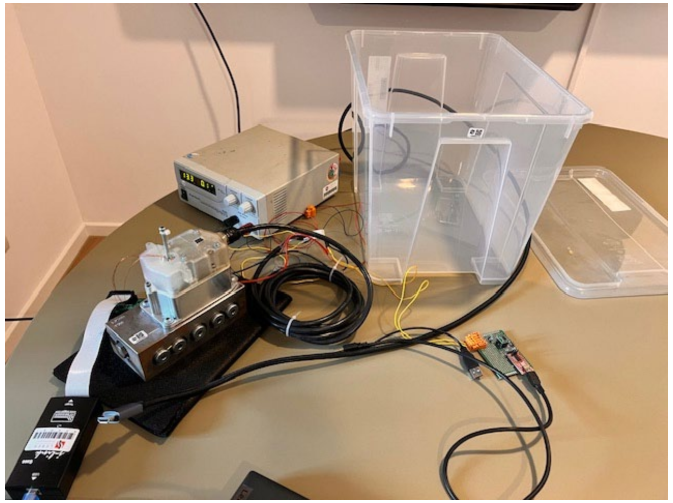
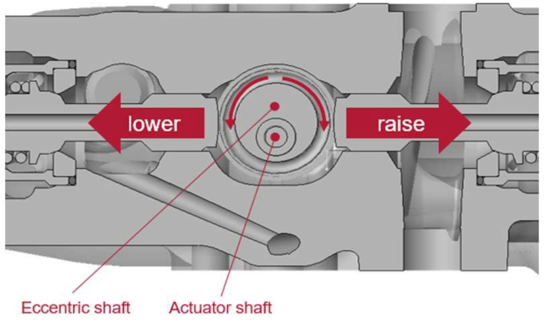
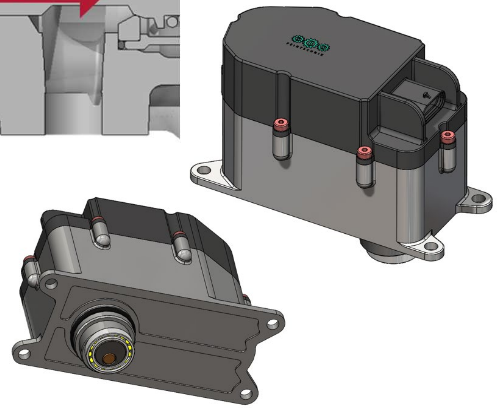


Roadmap

Controller replication







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Applications

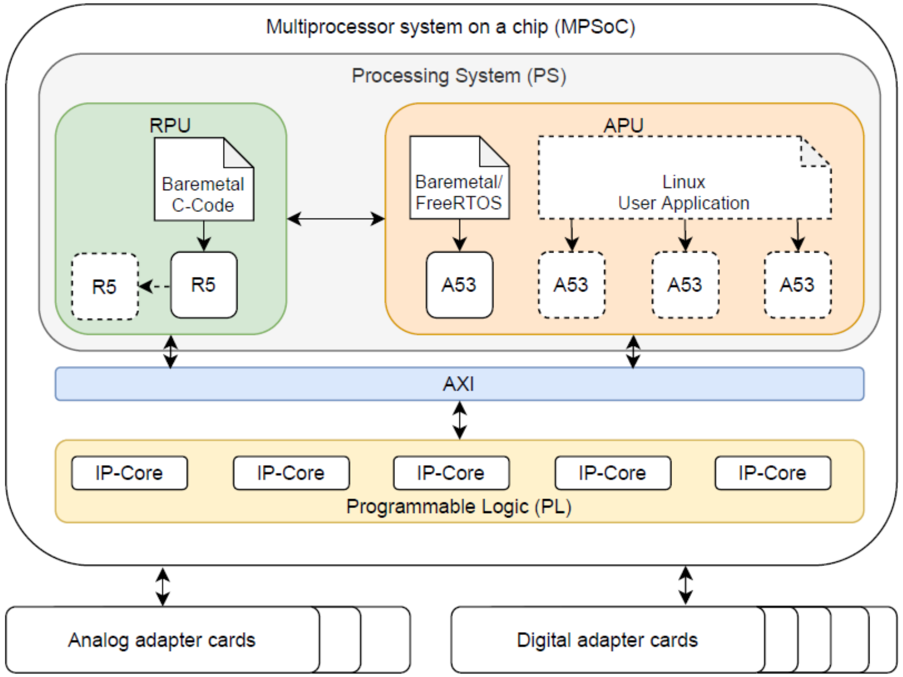
Actuator control power electronics and drive systems

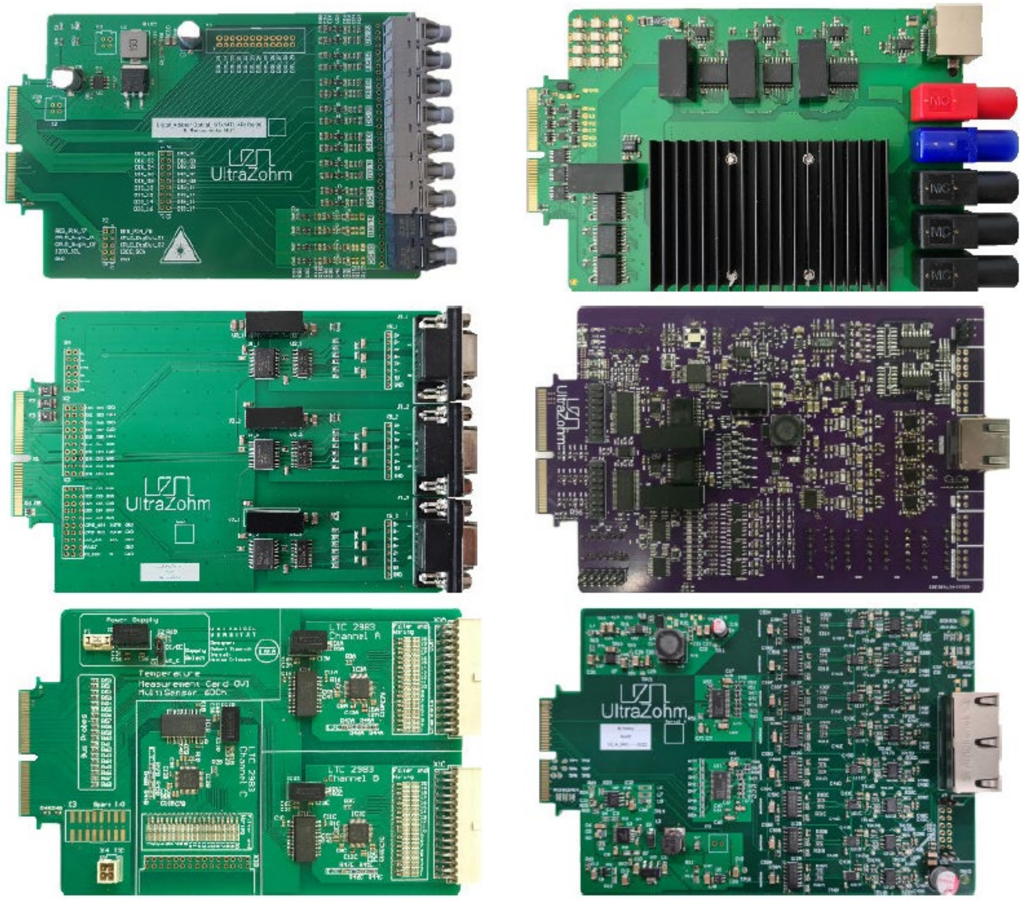
ANN/
SNN

ANN/
SNN

Roadmap

Controller replication





Collaboration: Tobias Schindler, Armin Dietz, ELSYS, OHM, UltraZohm Project Community

UltraZohm

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und Forschung

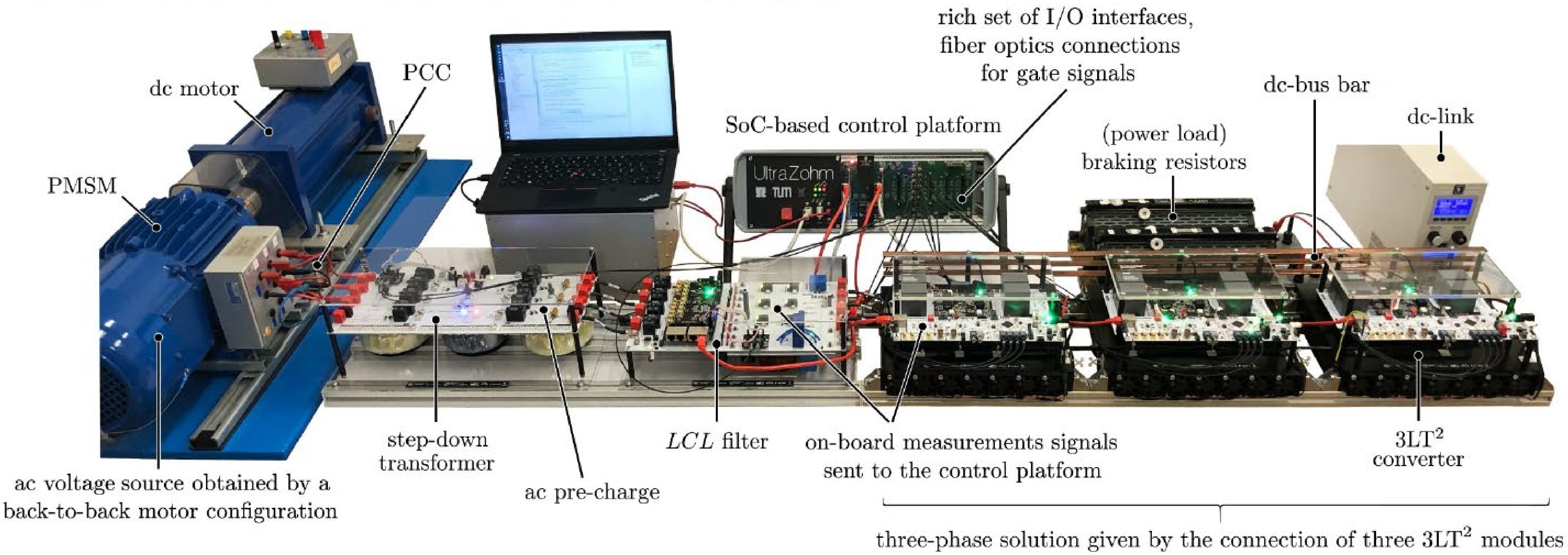
Applications
Actuator control power electronics and drive systems

ANN/ SNN

ANN/ SNN

Roadmap
Controller replication

Three-Level Neutral-Point-Clamped (NPC) Inverter
Picture by courtesy of Dr. Mattia Rossi at Politecnico di Milano, Italy.



Zohm Control GmbH
Intelligent Control Platforms and Algorithms

Collaboration: Tobias Schindler, Armin Dietz, ELSYS, OHM, UltraZohm Project Community

UltraZohm

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Applications

Actuator control power electronics and drive systems

ANN/ SNN

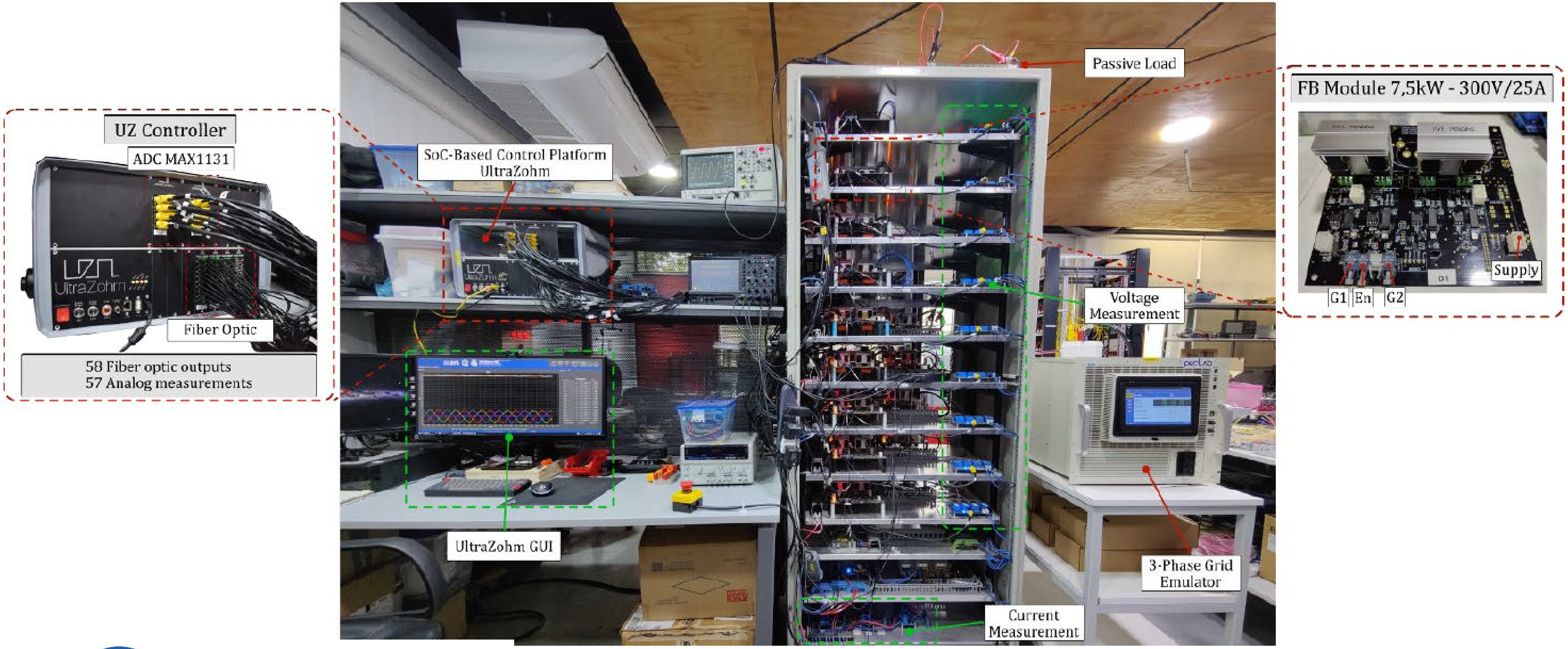
ANN/ SNN

Roadmap

Controller replication

Modular Multi-Level Matrix Converter (M3C) with 27 H-bridge cells

Picture by courtesy of Prof. Felix Rojas at Pontificia Universidad Católica de Chile, Chile.



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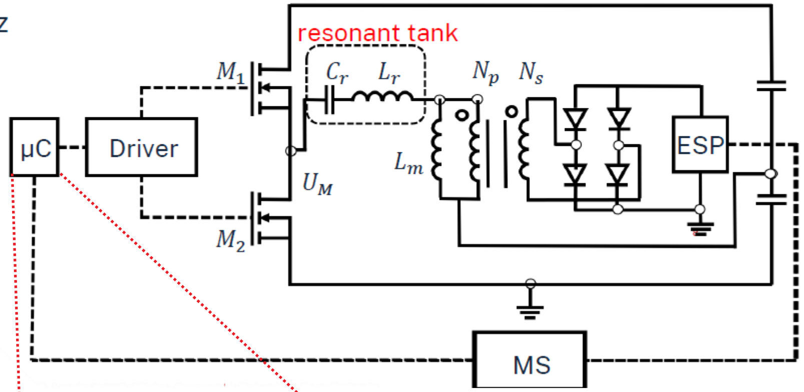
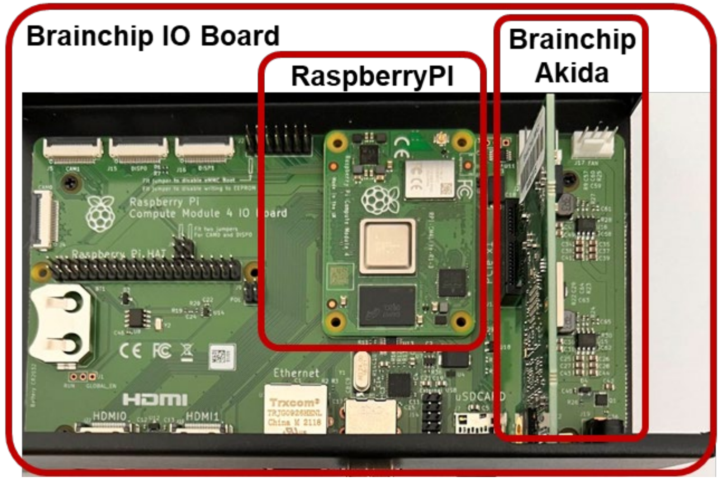
Applications

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





ANN/ SNN

Roadmap

Controller replication

Collaboration: Marcel Raum, Norbert Grass, ELSYS, OHM, Metallbau Greil

Applications

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

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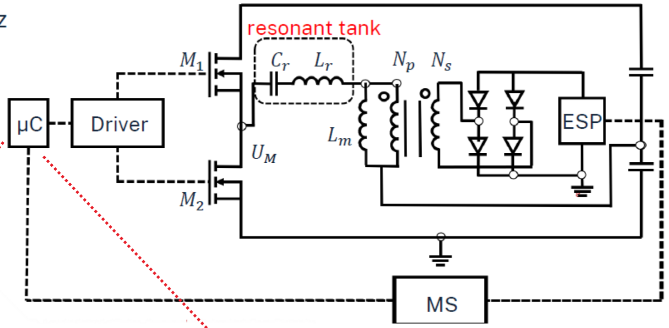
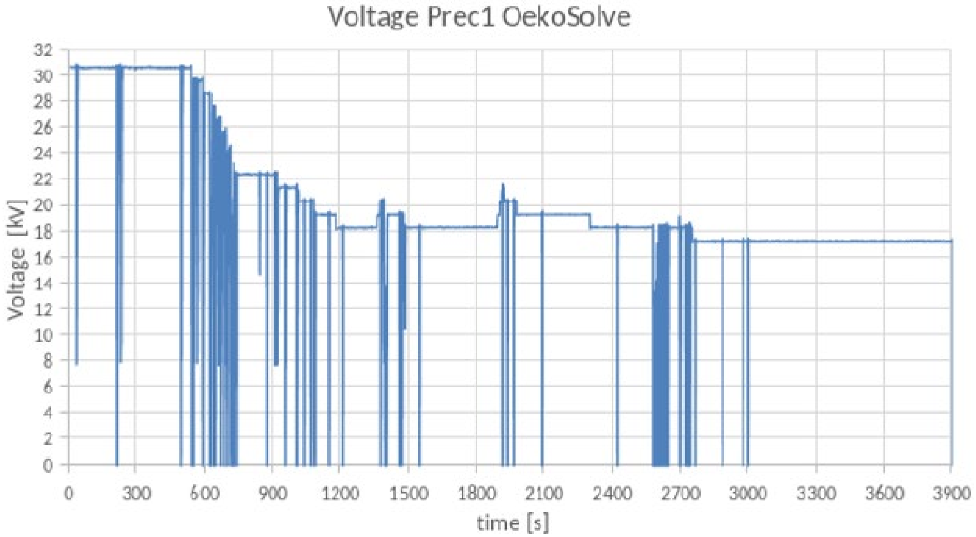
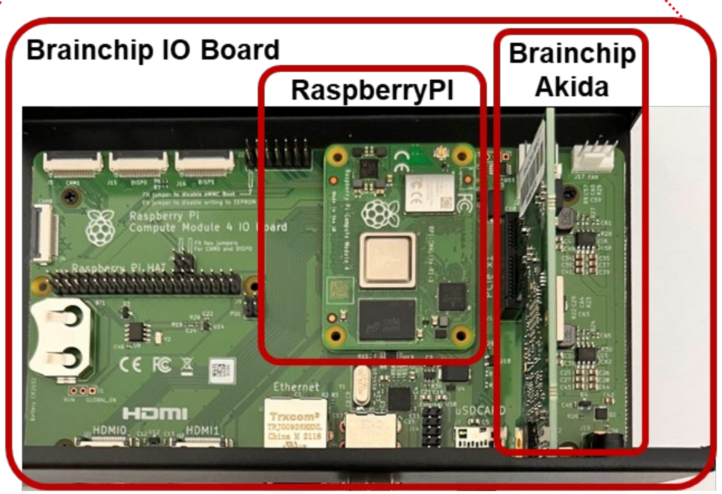
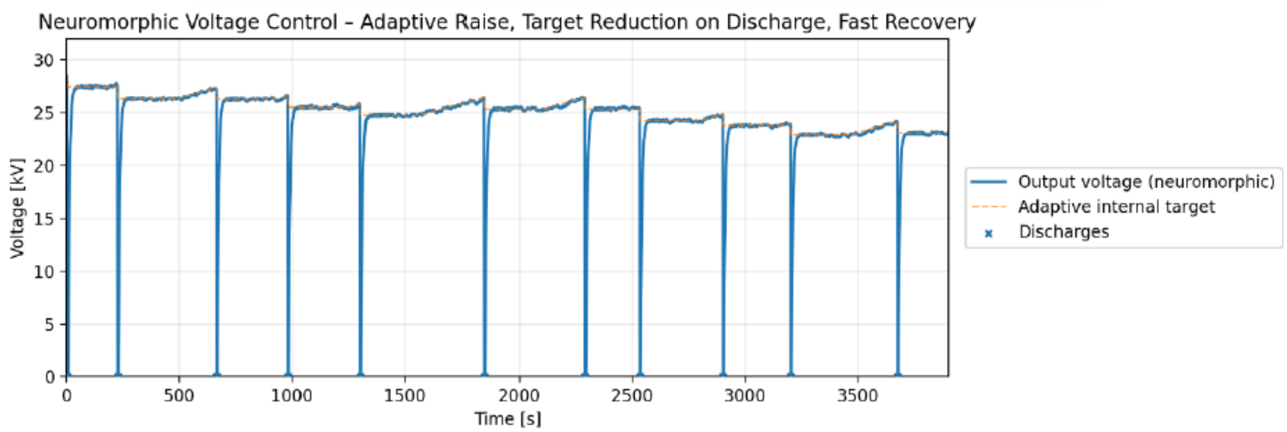




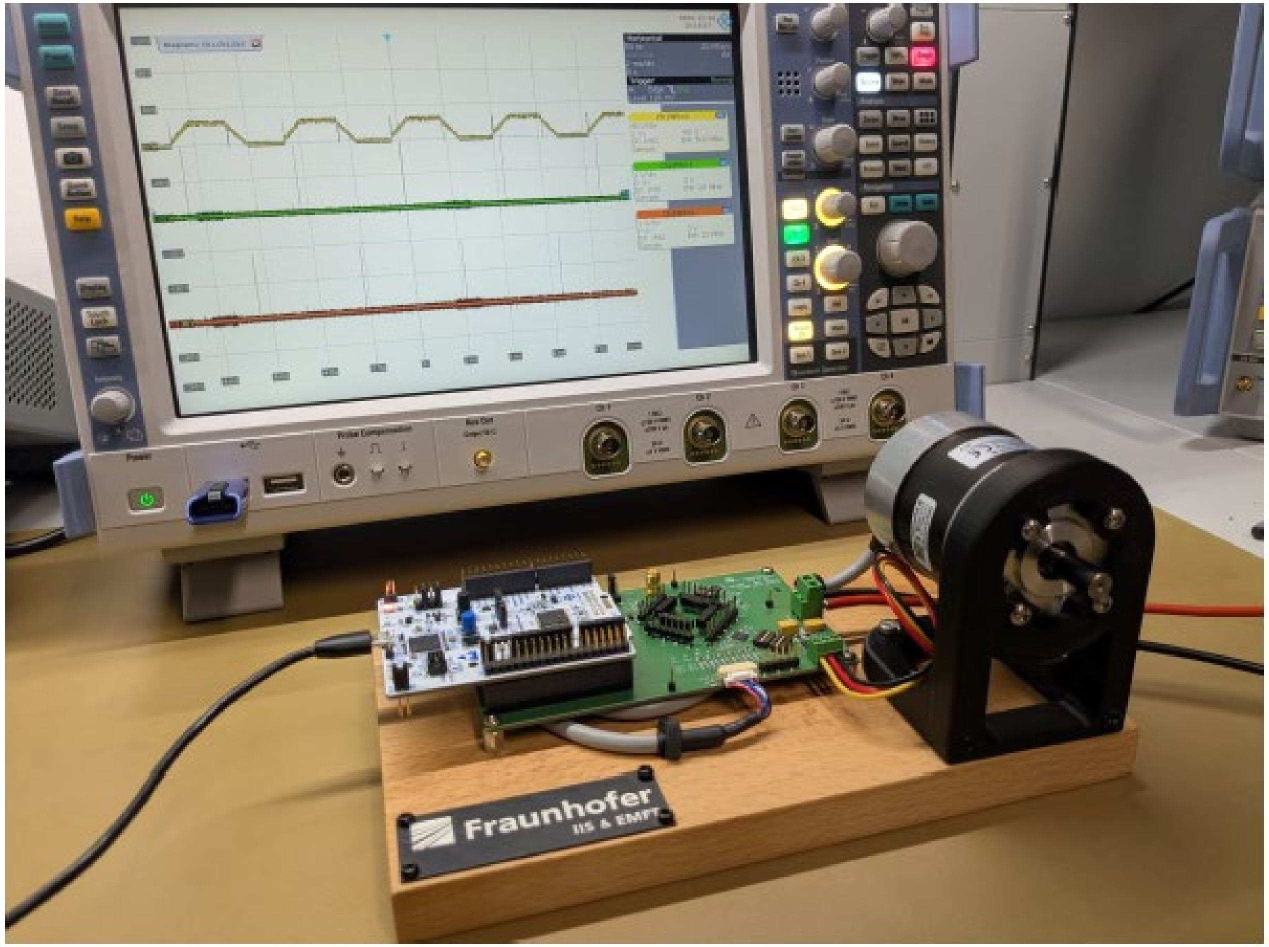




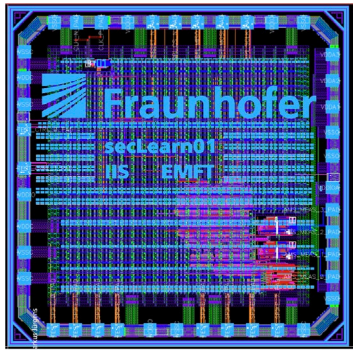
Collaboration: Marcel Raum, Norbert Grass, ELSYS, OHM, Metallbau Greil

Applications

Sensorless BLDC Field-Oriented-Control

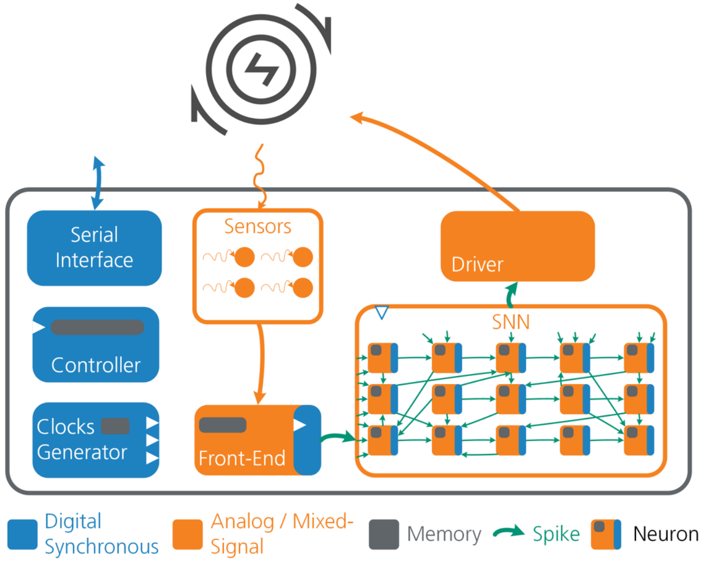


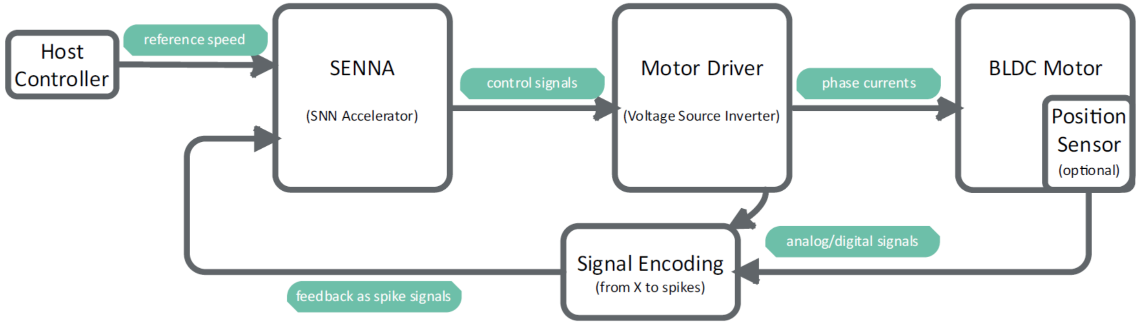
SNN



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 ≙ 10 mm²
  - Minimal Response Time: 20 ns, Energy efficiency: 500 fJ/SOP

With funding from the:

Federal Ministry of Research, Technology and Space

modulegnc quantum & neuromorphic computing

Collaboration: Andreas Stoll, Fraunhofer IIS and Ferdinand Pscheidl, Fraunhofer EMFT

Applications

Sensorless BLDC Field-Oriented-Control

SNN

Roadmap

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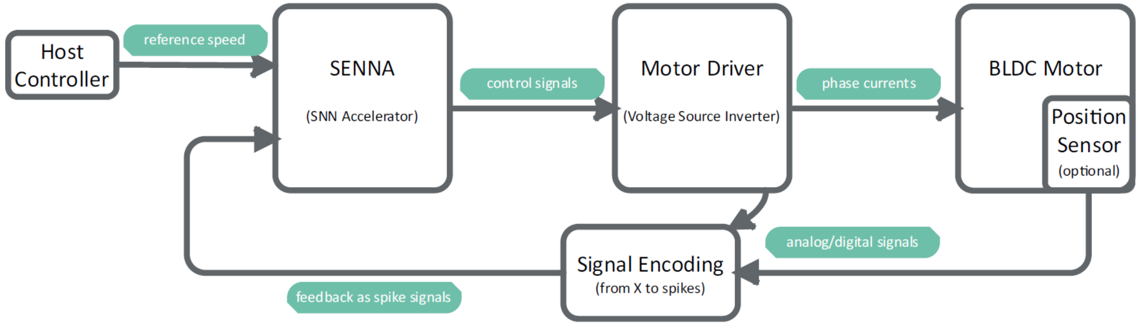

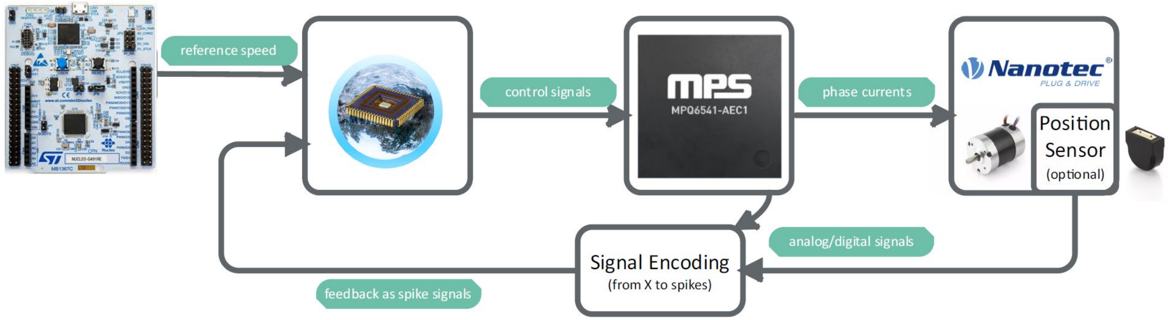

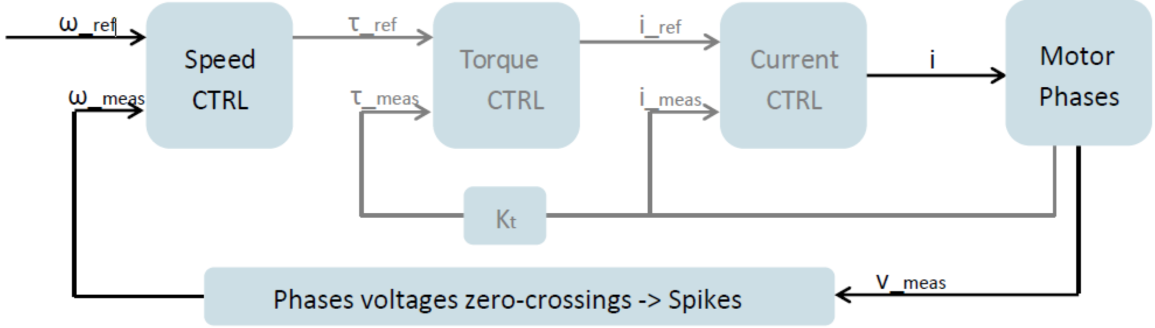

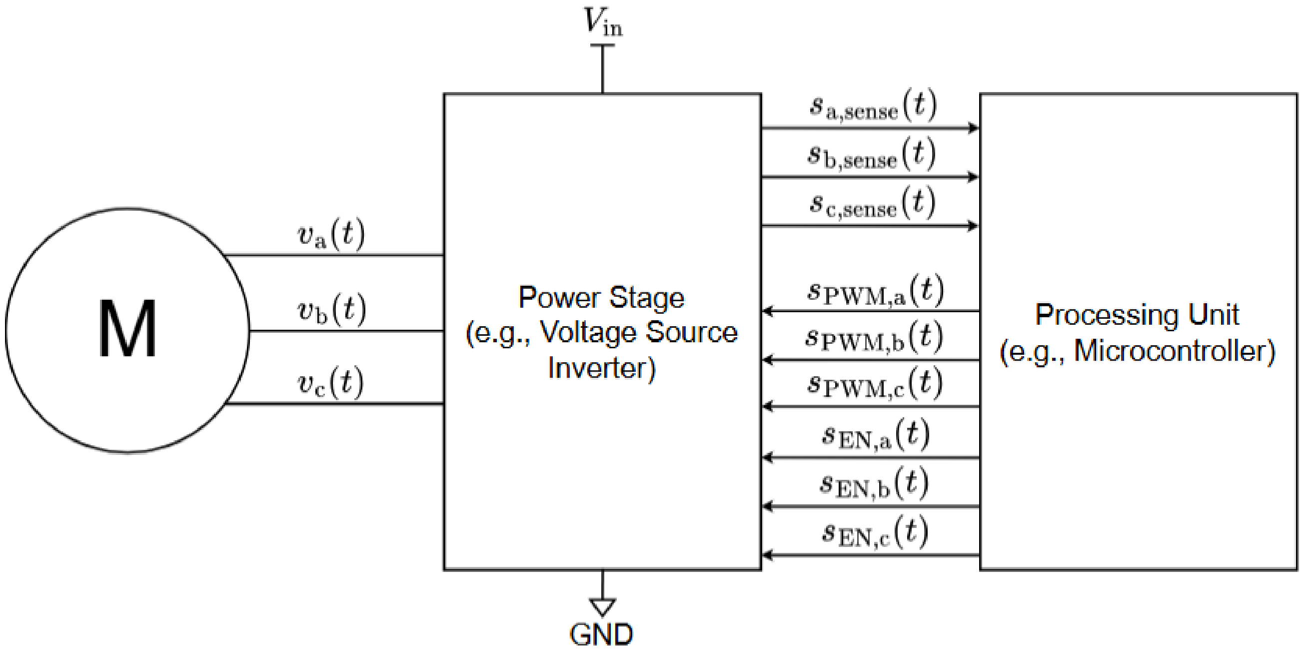

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Applications

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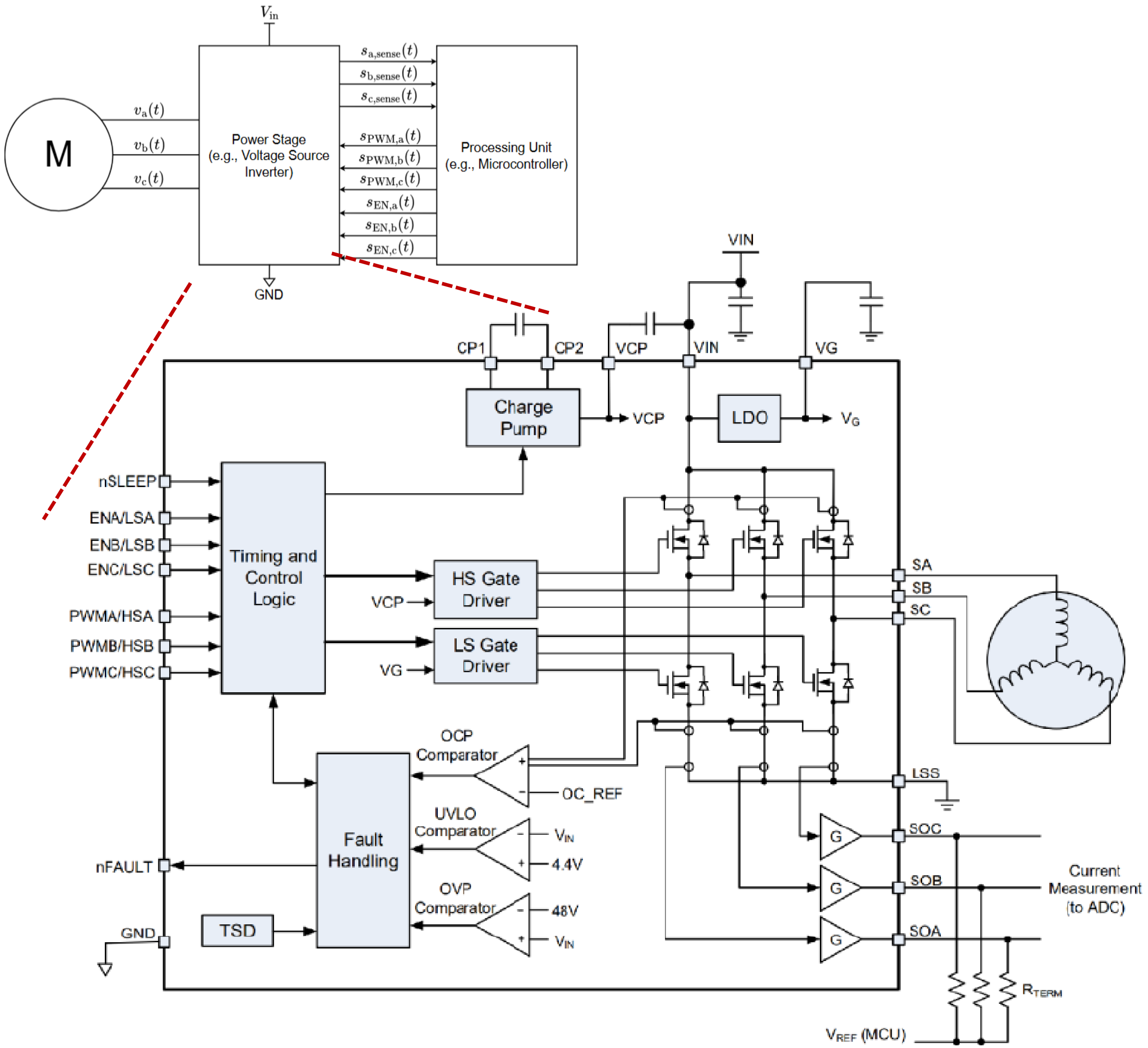
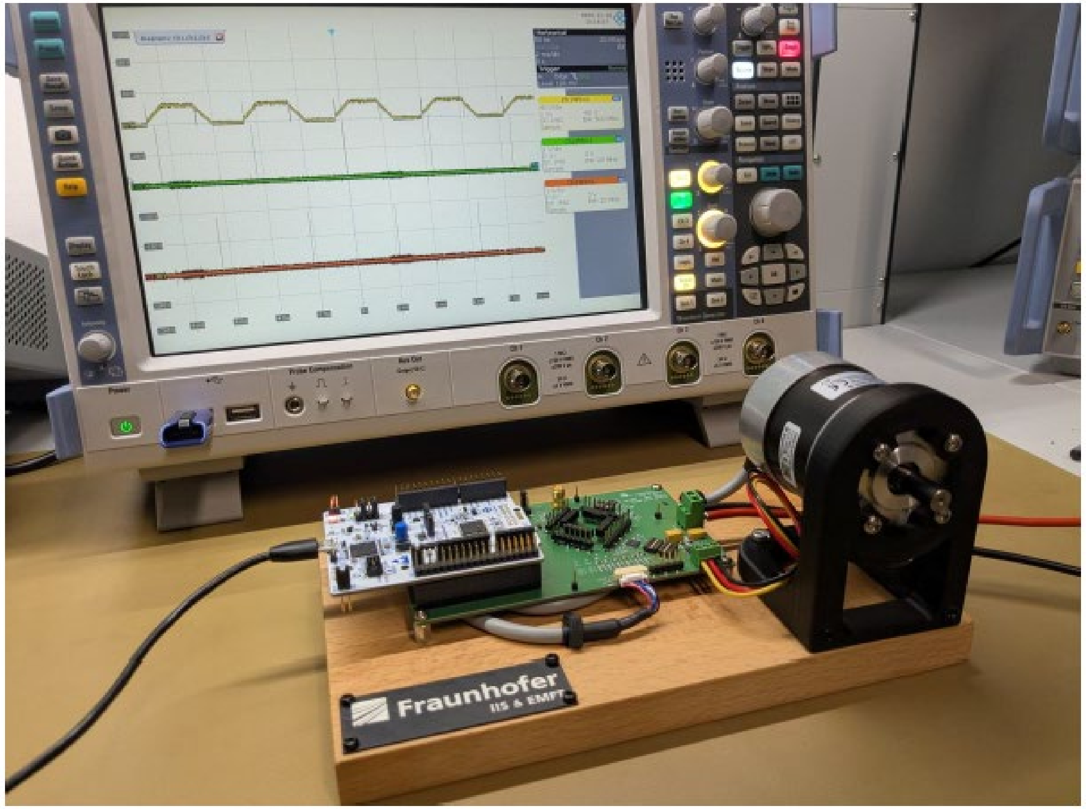


SNN

Roadmap

Standalone neuronal controller



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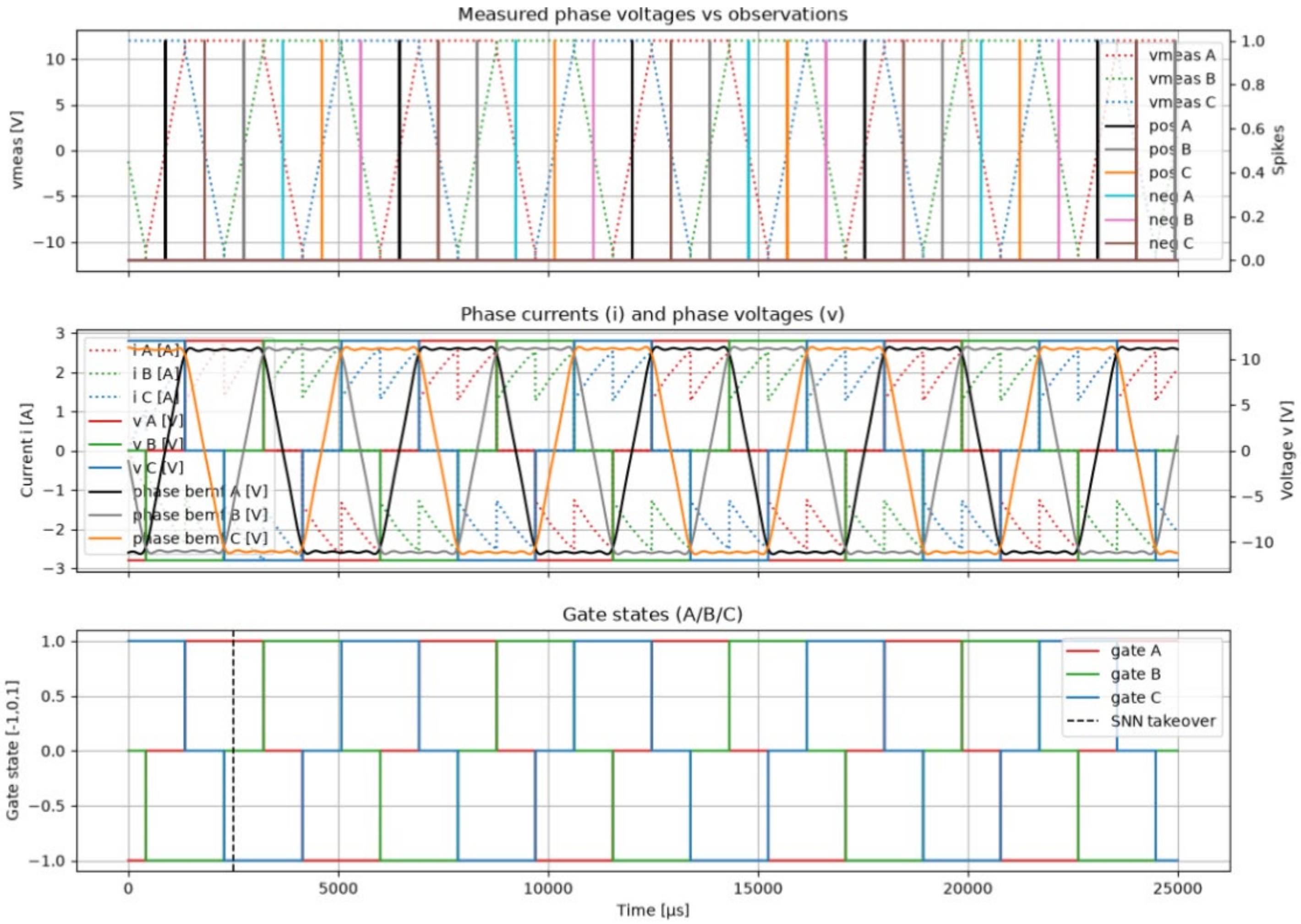
Applications

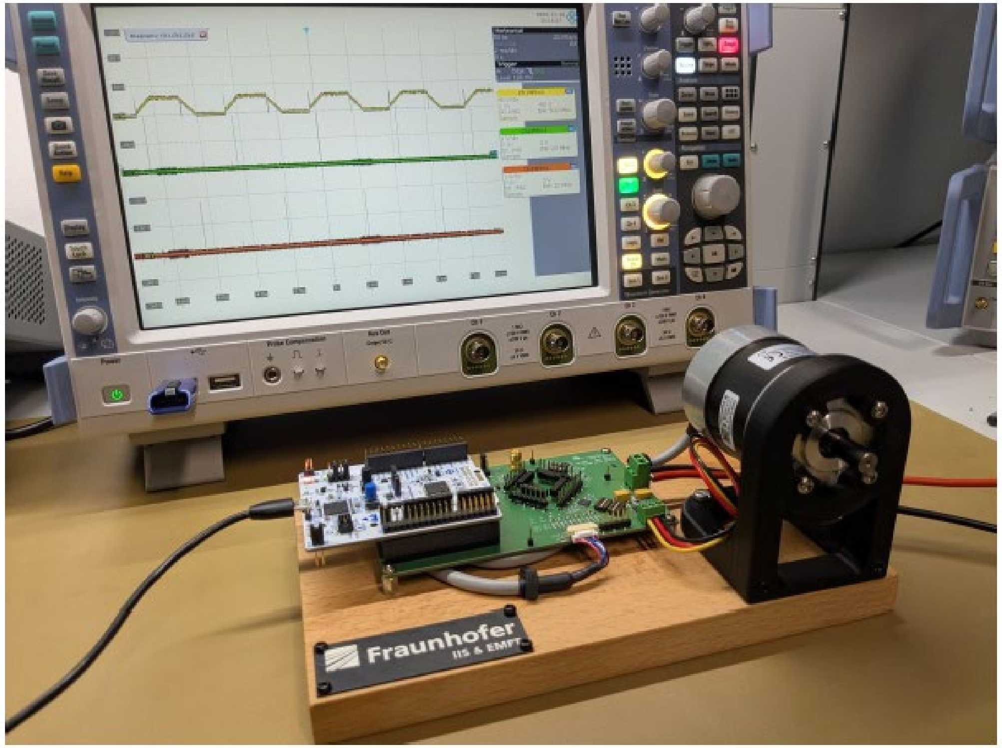
Sensorless BLDC Field-Oriented-Control



SNN

Roadmap

Standalone neuronal controller



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moduleqnc quantum & neuromorphic computing

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Benchmarking

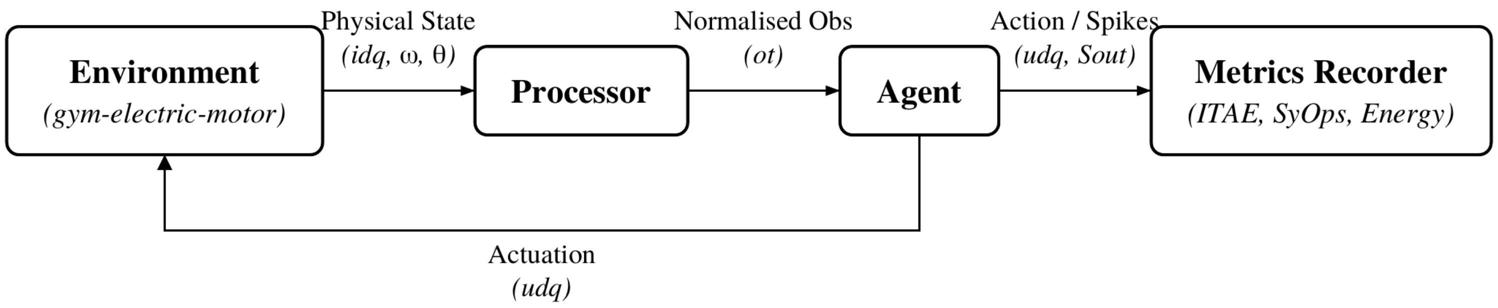
PMSM Field-Oriented-Control

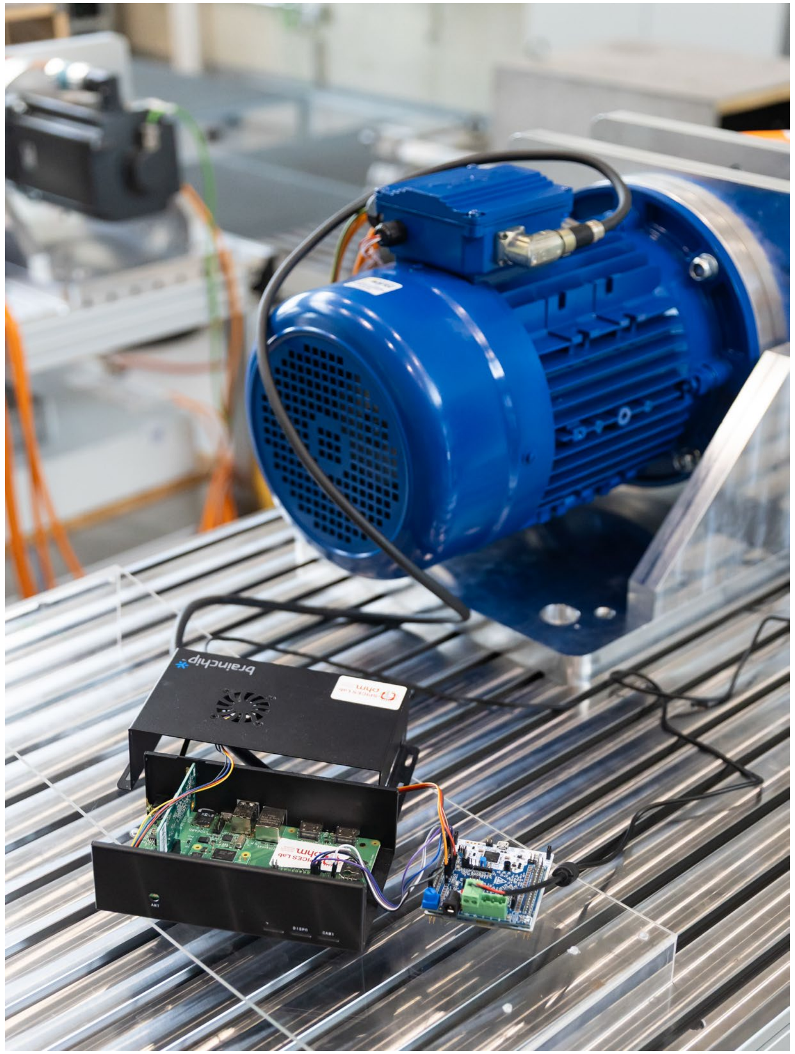
SNN

NeuroBench

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

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Fraunhofer IIS

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Benchmarking

PMSM Field-Oriented-Control

SNN

NeuroBench

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	$0 \to 2$	0.3
S2	Mid-speed Step	1500	$0 \to 2$	0.3
S3	High-speed Step	2500	$0 \to 2$	0.3
S4	Bidirectional Multi-step	1500	± 2 (4-st)	1.0
S5	Four-quadrant Trans.	1500	$+2 \to -2 \to 0$	0.9
S6	Field Weakening	2500	$0 \to 2$	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.

GEM/BDSIM simulates the PMSM, inverter, and mechanical load with a 10 kHz control step

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

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Benchmarking

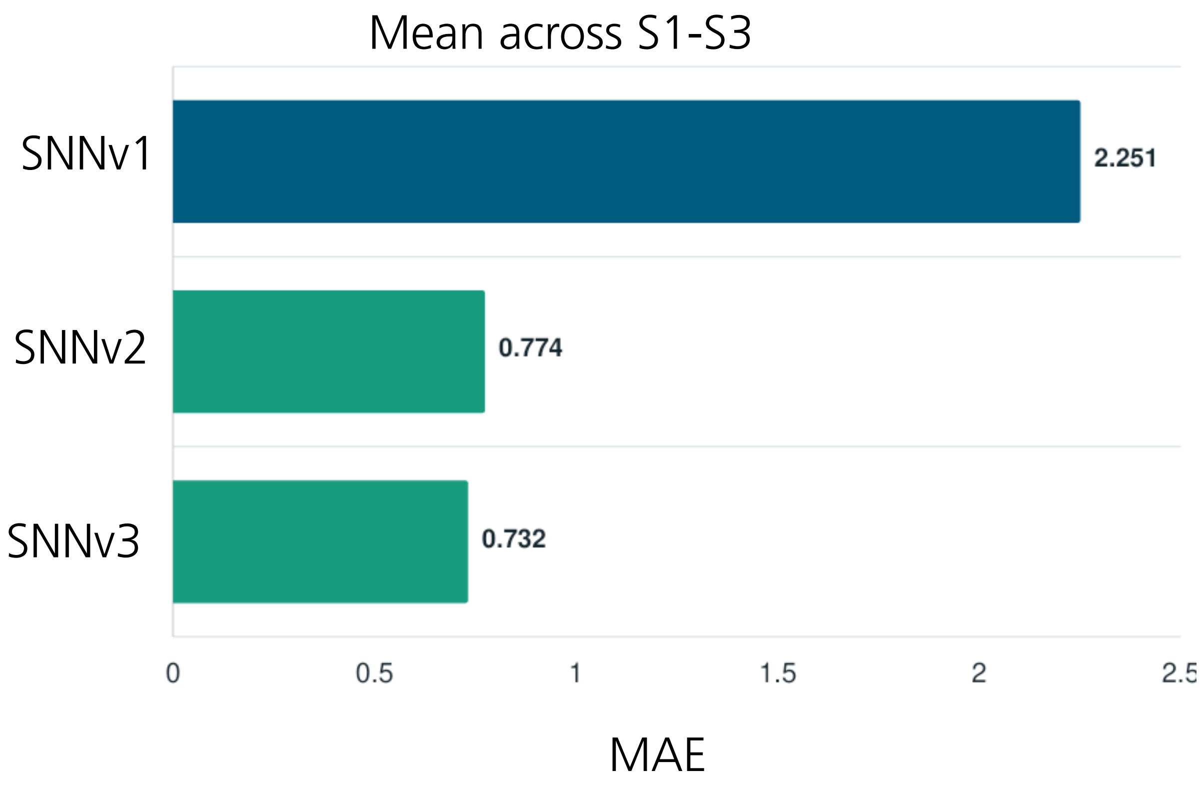
PMSM Field-Oriented-Control

SNN

NeuroBench

Ground-truth calibration separates controller quality

Mean MAE across the six scenarios reproduces the expected SNN ranking



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.

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Acknowledgments:
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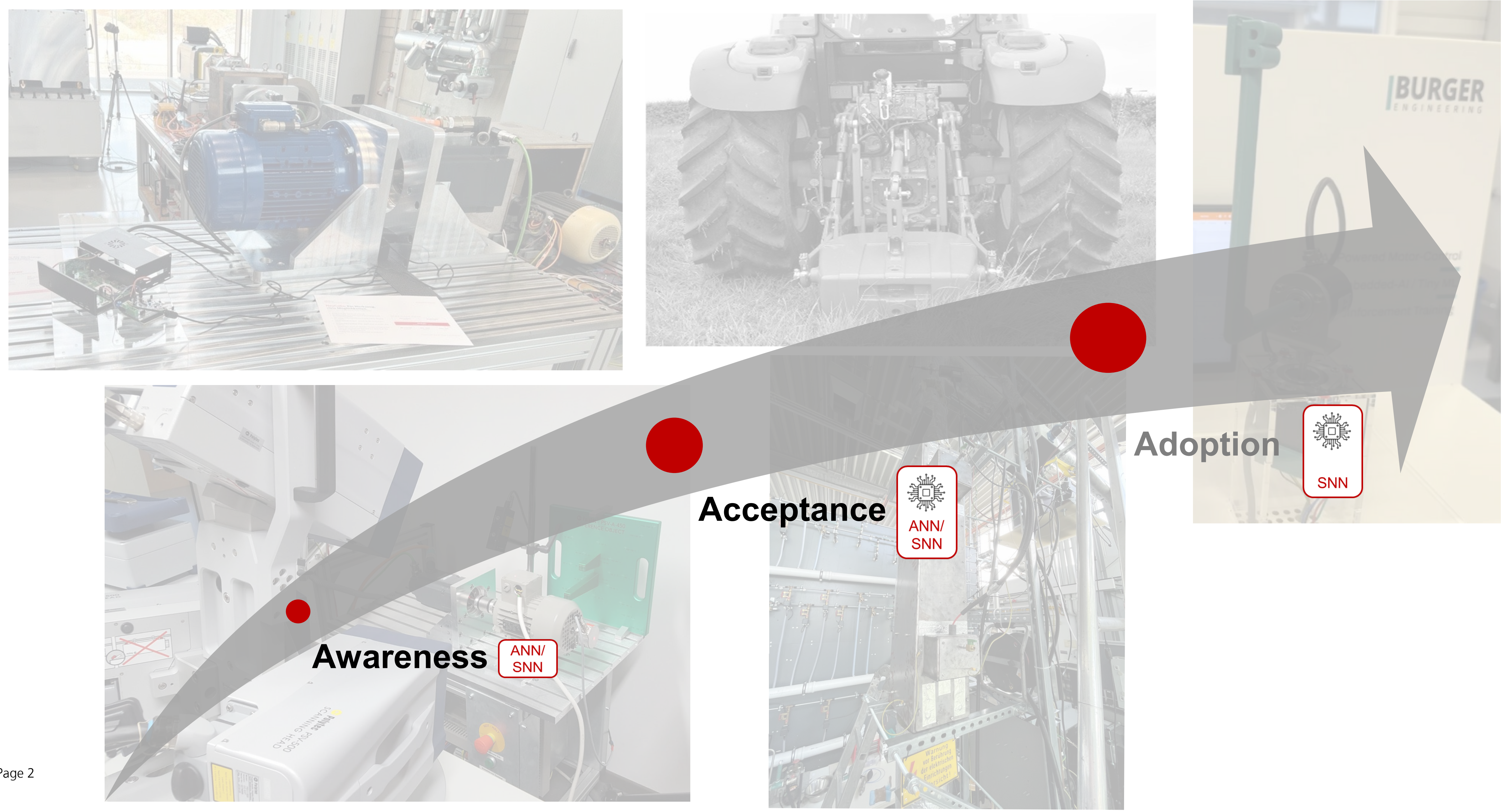
Control of power conversion systems



International initiatives

Regional initiatives

NeuroComp
Labs
NBay

Local initiatives

neuromorphics.bayern