



# **Einsatzgebiete künstlicher Intelligenz und Anwendung zur Steuerung von Erdbaugeräten**

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# Hochschule Osnabrück – Baubetriebstage 2024

## Einsatzgebiete künstlicher Intelligenz und Anwendung zur Steuerung von Erdbaugeräten

### Agenda

- Der Bosch Konzern und die Rolle der Forschung
- Forschung bei Bosch, weltweite Aufstellung
- Unser Campus in Renningen
- Anwendungen und Beispiele von KI bei Bosch
- Die Arbeitsgebiete der Gruppe CR/AAS4 (Advanced Autonomous Systems, Robotik)

# Who we are

## Our business sectors



**Mobility**



**Industrial Technology**



**Energy and Building  
Technology**

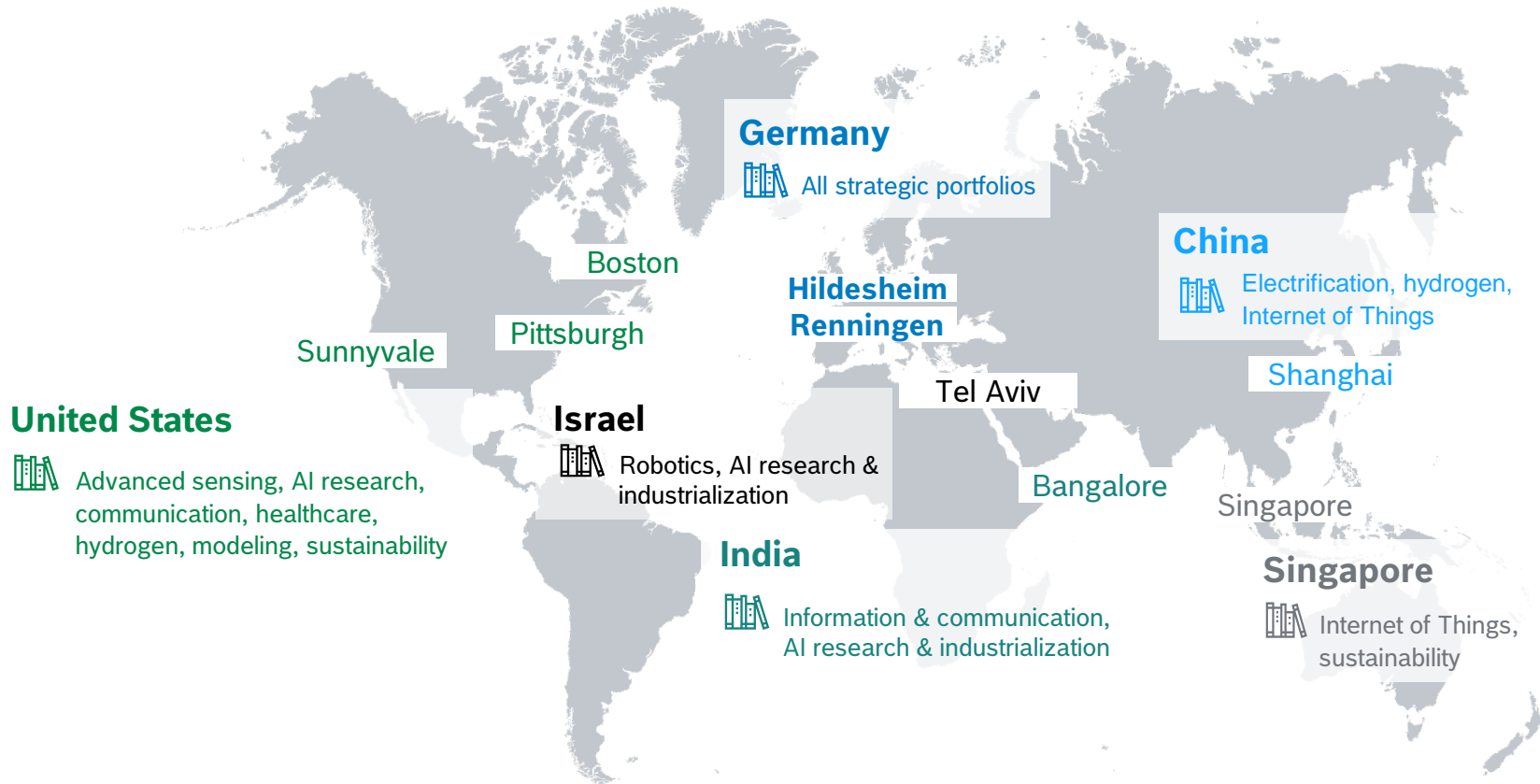


**Consumer Goods**

**Corporate Research (CR)**

# Bosch Research

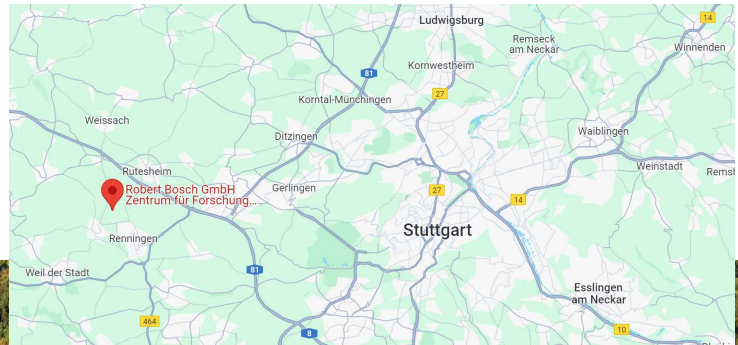
## Leveraging our international setup



-  **Connect to the best**
-  **Connect to RB local**
-  **Local Tech markets**
-  **Regional economics & talents**



# Renningen Research Campus Facilities



**2017**  
**Foundation Bosch Center for Artificial Intelligence**

**Chemistry, Stationary Fuel Cell**

**Analytics**

**AI, Cockpit Technologies**

**Workshop**

**Robotics, Production Technology**

**Vehicle Integration**

**Semiconductor Clean Room, Life Science Lab**

**Healthcare, X-Change Lab**

**Physics**

**Automated Driving**

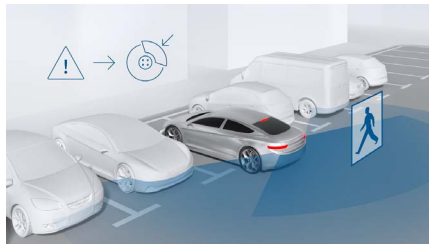
**Electric Drives, Mobile Fuel Cell**

**1500 Employees at Renningen  
200 AI specialists**

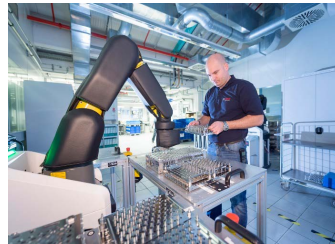


# Application areas of AI at Bosch

## AI-based Smart Products



Driver Assistance



Industrial Robotics



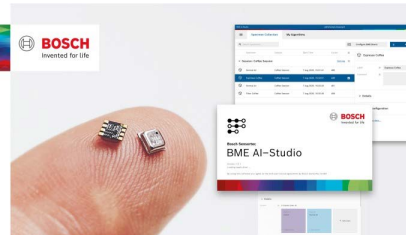
Home Robotics



Video Surveillance



Smart Home



Smart Sensors



Vivalytic (Diagnostics)



Software-defined Vehicle

### Search / Summarization

Make information accessible

### Chatbots

Facilitate interaction with customers

### Content Creation

Create high-quality documents, automatize tasks

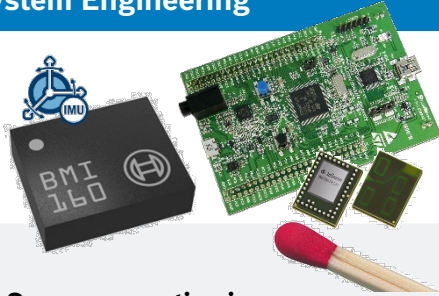
### Software Development

Automate code generation

# CR/AAS4: Sensing, Control & Motion

## Topics and Competency

### Sensors, Hardware, System Engineering



- ▶ **Sensor expertise in**  
GNSS, IMUs, Radar, Lidar, magnetic field sensors, mobile networks, etc.
- ▶ **Hardware and embedded software**  
Electronic design & test, low level drivers, Linux-enabled embedded systems, time-critical control applications
- ▶ **System Engineering**  
Design of complete robotic systems

**Programming**

### 3D-Renderings, Mechanical Design, Prototype Systems



- ▶ Design of **3D models** for robotic simulations (Blender)
- ▶ Construction and built up of mechanical components (CAD)
- ▶ Professional **3D-print** manufacturing
- ▶ Creation of **evaluation platforms**

**Sensor data fusion**

### Behavior and Motion Planning, Navigation



- ▶ **Path and motion planning**, optimization and integration, including **multi-agent path finding**
- ▶ **Navigation** and behavior control in mobile robotics
- ▶ Focus: Navigation in **industrial environments**  
e.g. DC ActiveShuttle

**e.g. obstacle avoidance**

# CR/AAS4: Sensing, Control & Motion

## Topics and Competency

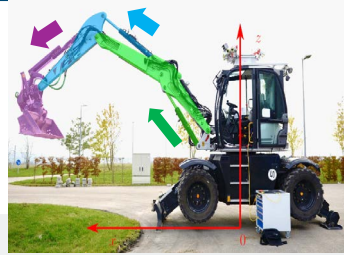
### Autonomous driving Test vehicle hardware



- ▶ **Control sub architecture** for autonomous driving with vehicles
- ▶ **Function development** of highly automated driving (HAD) features
- ▶ **System integration and testing**
- ▶ **HD-Map development**
- ▶ **Vehicle setup**  
Sensor and Hardware integration

**Sensor data fusion**

### Applied AI for Offroad Machinery & E-Mobility



- ▶ **Hybrid and data-based models**
- ▶ **Neural Ordinary Differential Equations (ODE)** for hybrid modelling
- ▶ Efficient Design of Experiment (DoE) & **Safe Active Learning**
- ▶ **Online learning** / adaptation of data-based controllers
- ▶ **Scalability:** Transfer functions to different systems & domains

**Control engineering**

### Manipulation and Control, Grasping, AI Based Methods



- ▶ **Control stack** for industrial robot arms
- ▶ Own AI-based software stack including **AI grasping**
- ▶ **Smart Item Picking (SIP)** for warehouse automation
- ▶ **Visual learning**

**Obstacle detection**

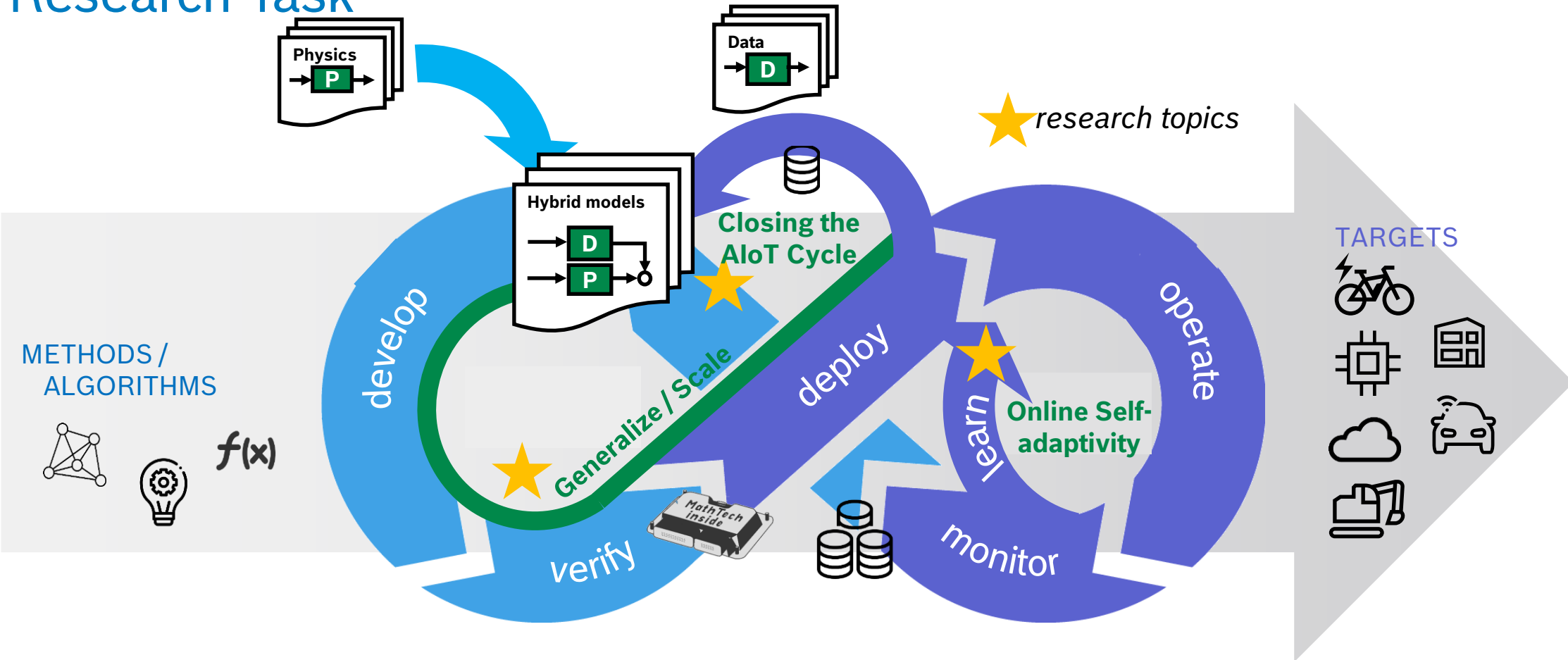




# Learning Hybrid Models for Smart Working Machines

Ozan Demir, CR/AAS4, 23.02.2024

# Learning Hybrid Models for Smart Working Machines Research Task



**Boost intelligence to create Self-Adaptive AIoT Products**

# Hochschule Osnabrück – Baubetriebstage 2024

## Einsatzgebiete künstlicher Intelligenz und Anwendung zur Steuerung von Erdbaugeräten

### Agenda

- Research Task: Create Self-Adaptive Products
- Lead Application: Learning Control for Mobile Machinery Assistance Functions
- Problem Setup & System Structure
- Research Questions:
  - DoE
  - Training Data-Based Controllers
  - Controller Design using Data-Based Models
  - **Online Adaptation of Data-Based Controllers**



# Learning Hybrid Models for Smart Working Machines

## Motivation

### Challenges:

- ▶ High requirements on assistance functions
- ▶ Complex and highly-nonlinear system dynamics
- ▶ Systems with unknown (non-Bosch) components
- ▶ Production tolerances, environmental effects, aging
- ▶ Low volume & high mix domain

### Tasks:

- ▶ Reduce the time to apply the control strategy on a new machine
- ▶ Reduce the calibration effort for different variants of the same machine
  - ▶ Online fine-tuning on the target device
- ▶ Providing tools for better usability and reproducibility of the learning pipeline



# Learning Hybrid Models for Smart Working Machines

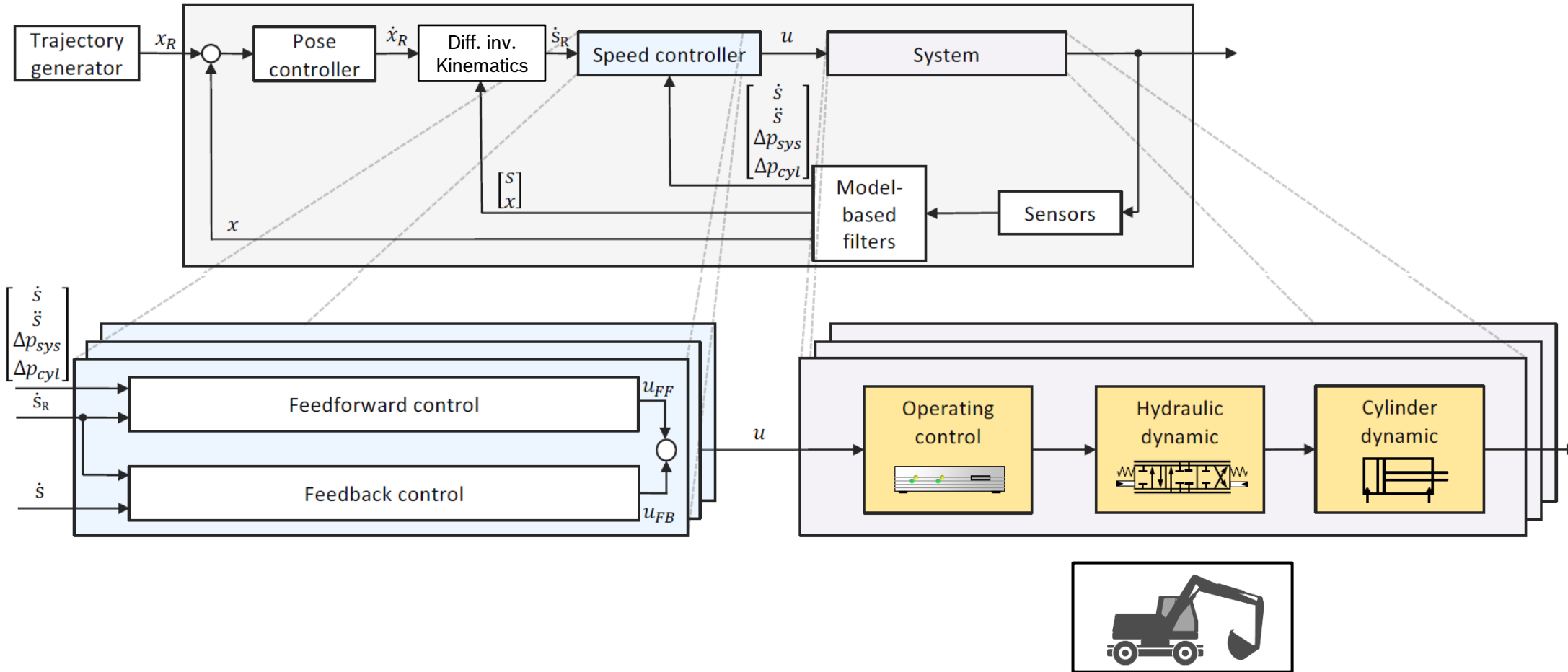


**Fast & accurate**  
path following for  
smart **working machines**

Link to Video:  
[YouTube](#)  
[BoschTube](#)

# Learning Hybrid Models for Smart Working Machines

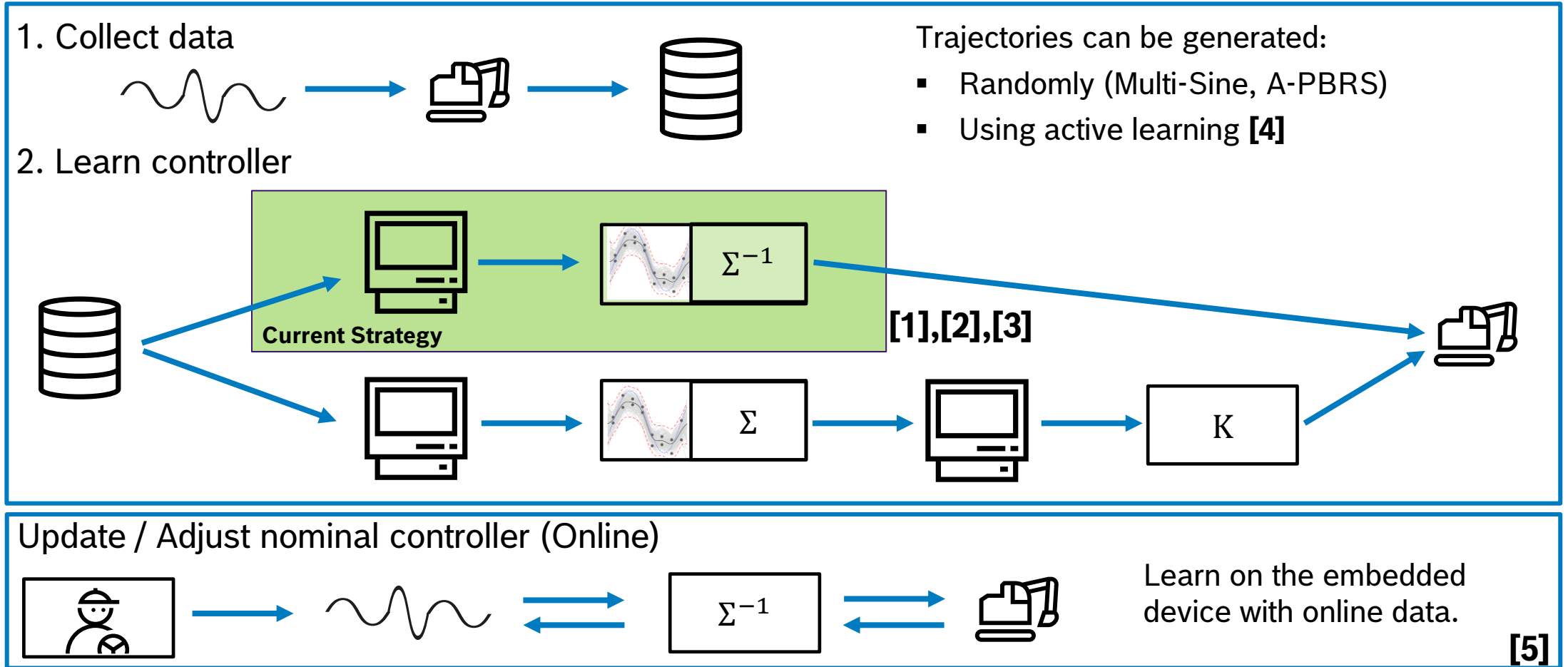
## System Structure





# Learning Hybrid Models for Smart Working Machines

## From Data to Control – 2 approaches



# Learning Hybrid Models for Smart Working Machines



Learning control using  
**hybrid models** for smart  
**working machines**

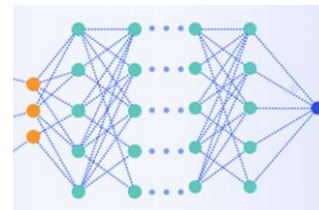
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[BoschTube](#)

# Learning Hybrid Models for Smart Working Machines

## Solution approach (I): Learning a hybrid controller

- Replace model-based hydraulics-controller with AI model  
→ **hybrid control structure**

- Training pipeline:
  - collect 2-3h of data
  - train data-based models on PC
  - write back to embedded SW



State-of-the-Art AI-model  
(Deep neural network)



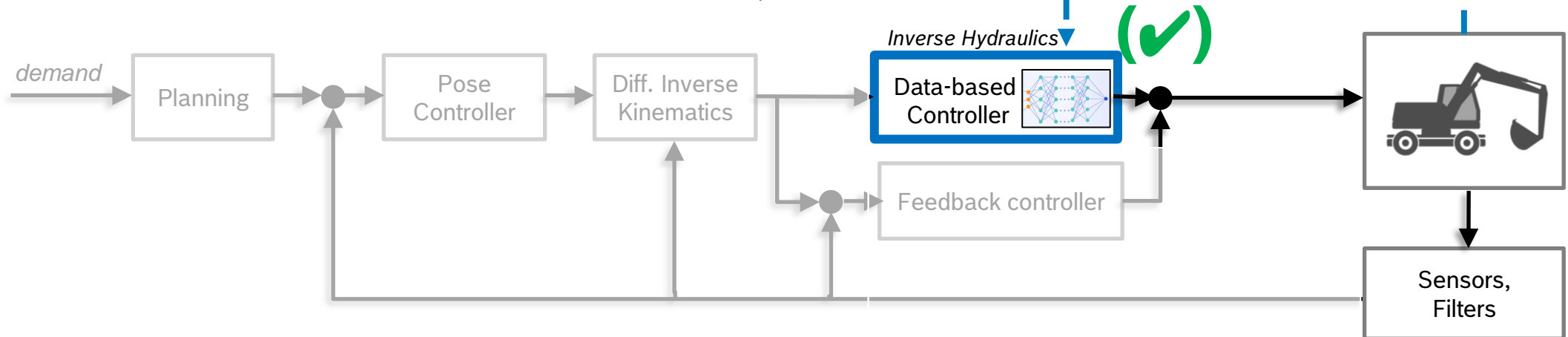
Effort:

**5-20h**

per iteration; not suitable for

- fast engineering iterations ⚡
- EoL calibration ⚡
- aging compensation ⚡

**On-device training  
required!**





# Learning Hybrid Models for Smart Working Machines

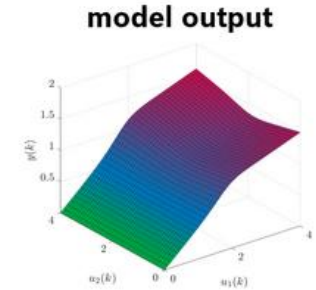
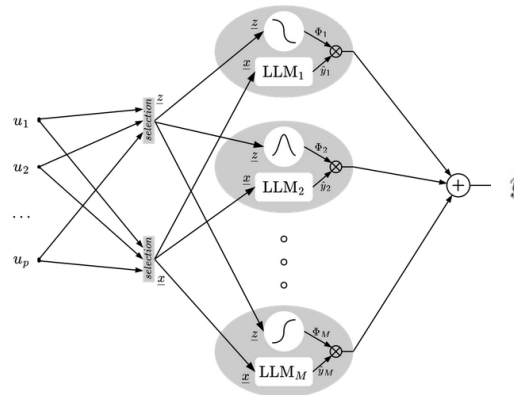
## Solution approach (II): Online Learning (Adaptation)

### Challenges for on-device learning:

- **Limited resources** (memory, computation)
- **Classical machine learning approaches not possible** (high-dimensional optimization problem)

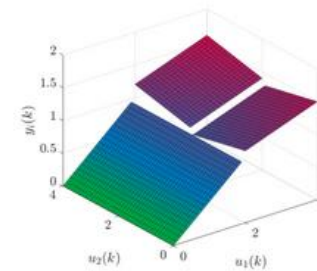
### Solution:

- **Adaptive control** using “**Local model networks**”
- Two-stage learning:
  - Offline: **input space partitioning** (validity functions), incorporation of expert knowledge possible
  - On-device: **recursive adaptation** of local models weights

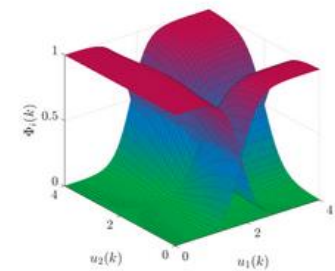


$$\hat{y} = \sum_{i=1}^M \hat{y}_i(\underline{x}) \Phi_i(\underline{z})$$

local models  $\hat{y}_i(\underline{x})$



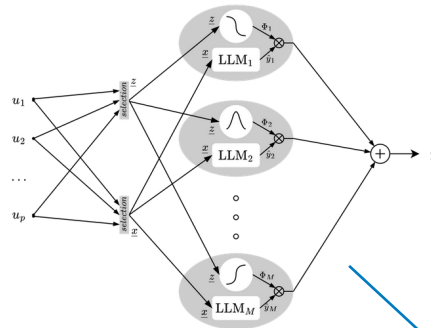
validity functions  $\Phi_i(\underline{z})$



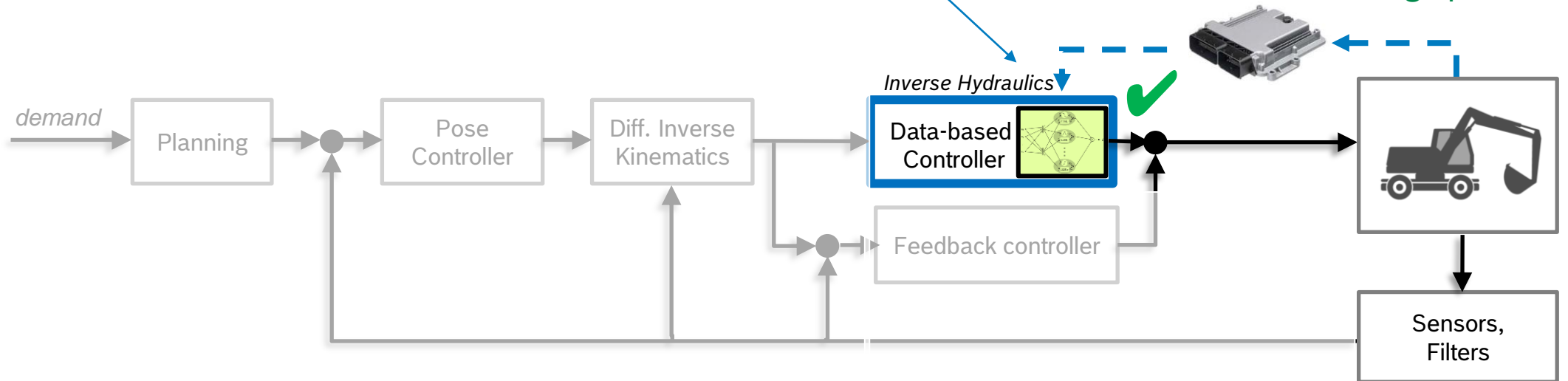
# Learning Hybrid Models for Smart Working Machines

## Solution approach (II): Online Learning (Adaptation)

Implementation of local model networks and online adaption



Effort:  **minutes**  
training on ECU during operation



# Learning Hybrid Models for Smart Working Machines

## Further Work

[1] „Hybrid data-driven modelling for inverse control of hydraulic excavators,” in Proceedings of the International Conference on Intelligent Robots and Systems (IROS), 2021, J. Weigand, J. Raible, N. Zantopp, O. Demir, A. Trachte, M. Ruskowski

[2] „Data-Driven Feed-Forward Control of Hydraulic Cylinders using Gaussian Process Regression for Excavator Assistance Functions“, in Conference on Control Technology and Applications (CCTA), 2022, G. Rabenstein, O. Demir, A. Trachte, K. Graichen

[3] „Learning Based Feed-forward Control for Advanced Excavator Assistance Functions”, in Int. Fluid Power Conference (IFK), 2022, O. Demir, B. Ehlers, F. Bender, A. Trachte

[4] “Safe Active Learning and Probabilistic Design of Experiment for Autonomous Hydraulic Excavators“, in Proceedings of the International Conference on Intelligent Robots and Systems (IROS), 2023, M. Dio, O. Demir, A. Trachte, K. Graichen

[5] “Online Learning of Cylinder Velocity Controllers for Excavator Assistance Functions using Local Model Networks“, in Int. Fluid Power Conference (IFK), 2024, O. Demir, B. Hartmann, N. , F. Bender, B. Ehlers, M. Mehren

**Thanks for your interest!**