Karlsruhe Institute of Technology

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# Accelerated Deep Reinforcement Learning for Fast Feedback of Synchrotron Beam Dynamics

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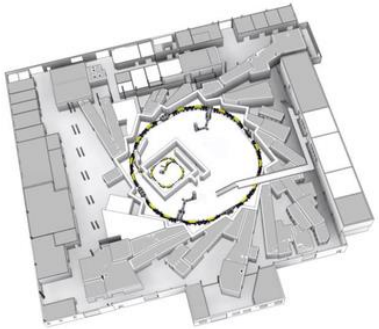
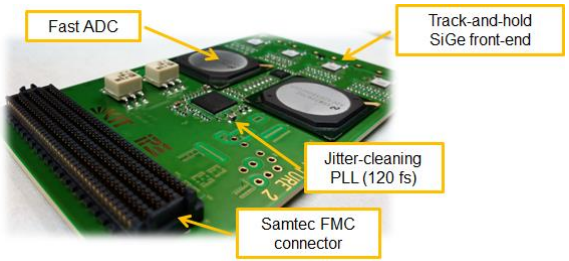


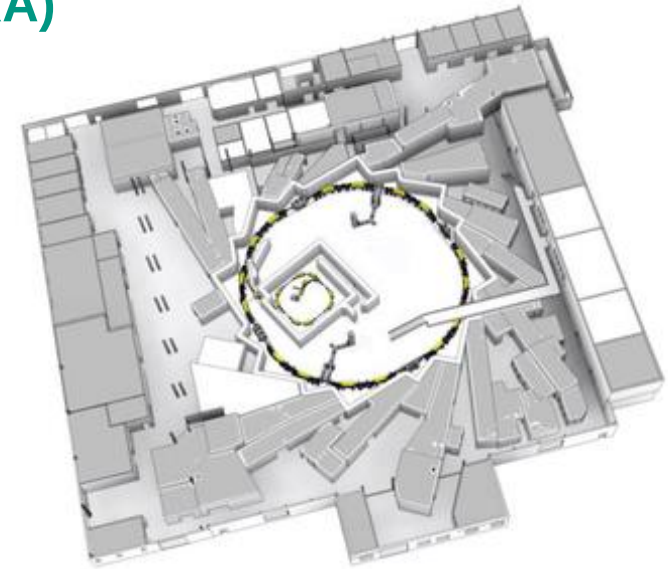


# Outline

- Motivations
- Requirements
- Hardware development
  - Front-end electronics for fast THz detectors
  - Fast feedback hardware implementation
- Real-time data processing by AI
  - Introduction of Reinforcement Learning
  - Real-time implementation
- Preliminary results
- Conclusions and what's next

# Accelerator Facilities at KIT

## Karlsruhe Research Accelerator (KARA)



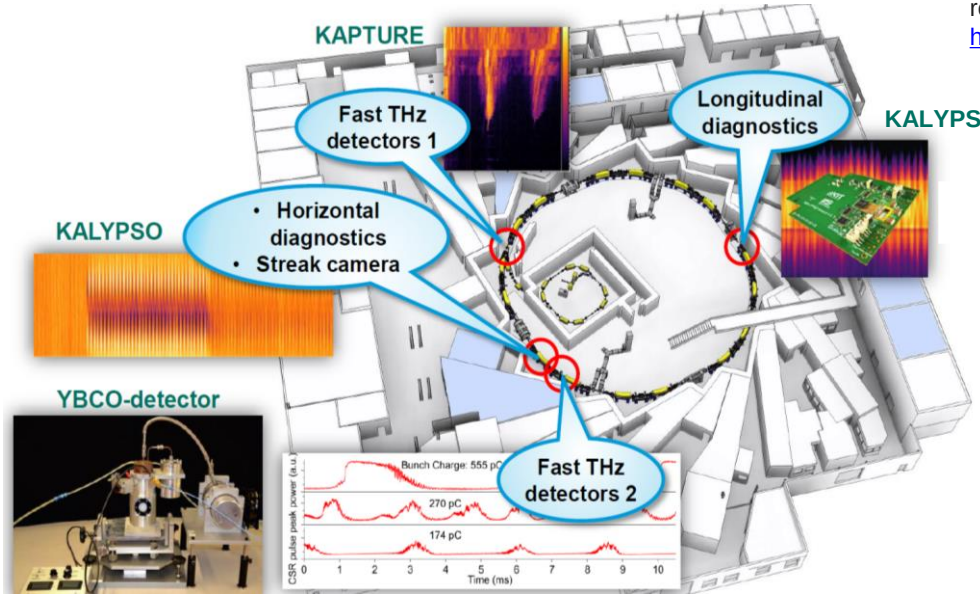
### Electron storage ring and Synchrotron light source

- Circumference: 110.4 meters
- Energy range: **0.5 - 2.5 GeV**
- Platform for development and testing of new beam and acceleration technologies
- Pooling research of new accelerator concepts
- Development of new detectors

# Karlsruhe Research Accelerator (KARA)

Caselle M., et al. KAPTURE-2. A picosecond sampling system for individual THz pulses with high repetition rate. JINST (2017), DOI: 10.1088/1748-0221/12/01/C01040

Rota, L., Caselle M., et al. KALYPSO: Linear array detector for high-repetition rate and real-time beam diagnostics. NIM A (2018), DOI: https://doi.org/10.1016/j.nima



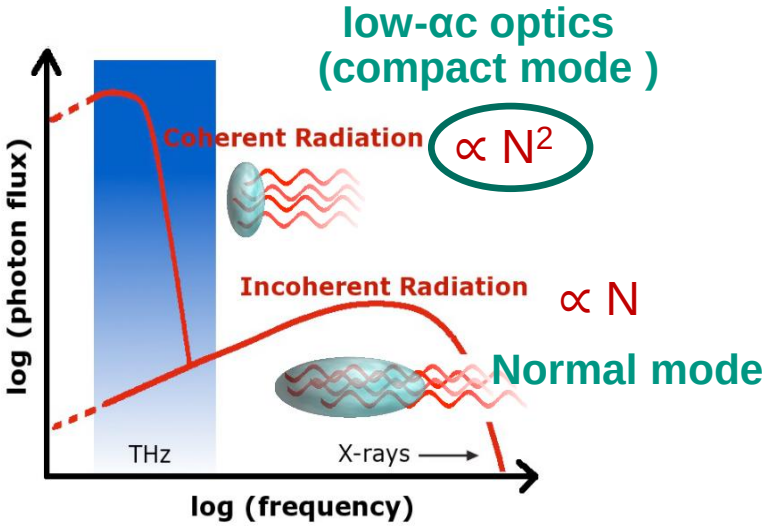

- KARA: one of the 1st to offer short bunch
- (low-$\alpha_c$ optics) bunch length down to few ps
- Enable to study the microbunching instability
- Custom detectors developed for a real-time resolved phase space tomography

Kehrer B., et al. Synchronous detection of longitudinal and transverse bunch signals at a storage ring. *Phys. Rev. Accel. Beams (2018),* 102803

# Coherent Synchrotron Radiation (CSR)

## Generation of CSR

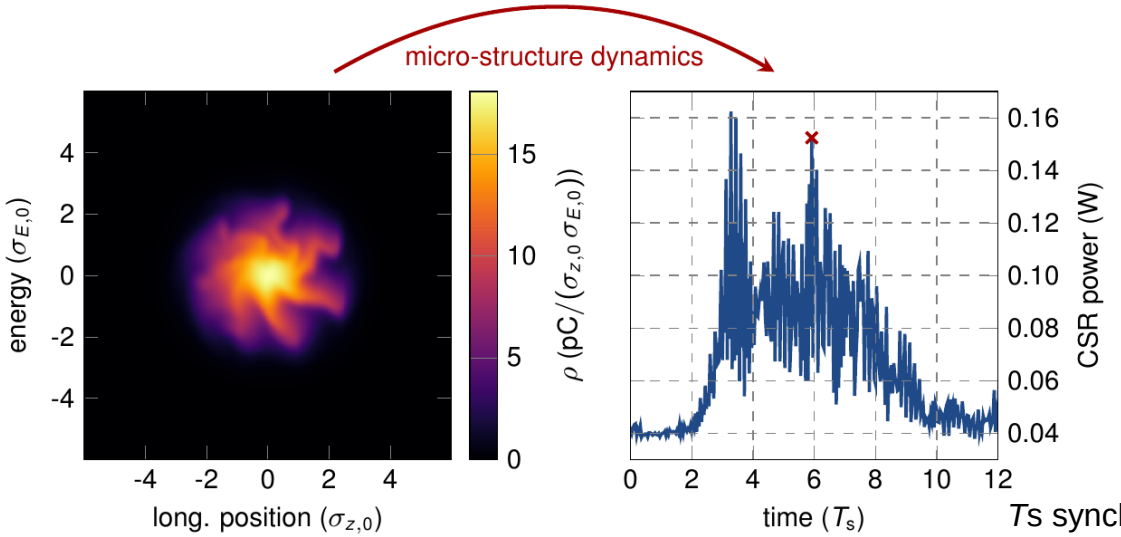
- When the wavelength of the emitted radiation is considerably shorter than the bunch length ($\lambda \ll \sigma_z$), the synchrotron radiation is emitted coherently
- CSR = high radiation power
  - → interesting for users!
  - → operation in short bunch mode (low $\alpha_c$ optics)
- **Short bunch mode → microstructures appear, making the CSR power fluctuate**
- Goal: CSR stabilization with high average (power) and low variance




A.-S. Müller, et al. “Experimental Aspects of CSR in the ANKA Storage Ring” ICFA Beam Dynamics Newsletter (2012), No. 57, 154–165

# KARA and Micro-bunching instability

- High intensity of CSR power
- Complex dynamics of the bunch makes the control challenging
- Real-time control with latency down to few hundred of μs




**GOAL: Control the Micro-bunching instability by Machine Learning**

$T$s synchrotron oscillation period of 7 kHz

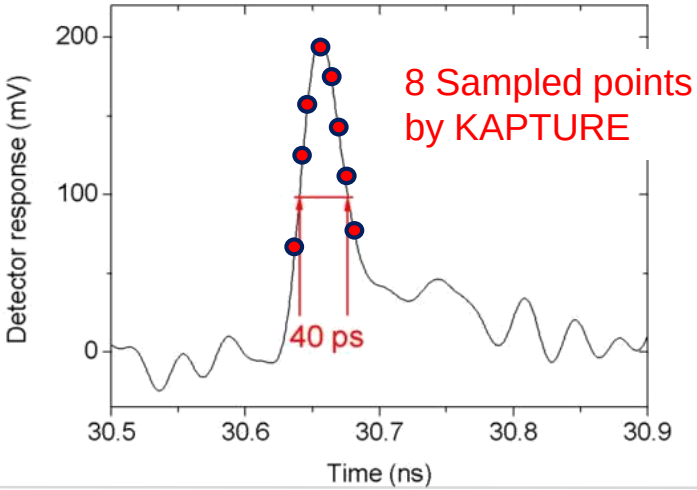
# KAPTURE - Measurement of bunch properties

## Karlsruhe Pulse Taking Ultra-fast Readout Electronics (KAPTURE)

KAPTURE is an ultra-wideband front-end electronics for ultra-fast Terahertz detectors

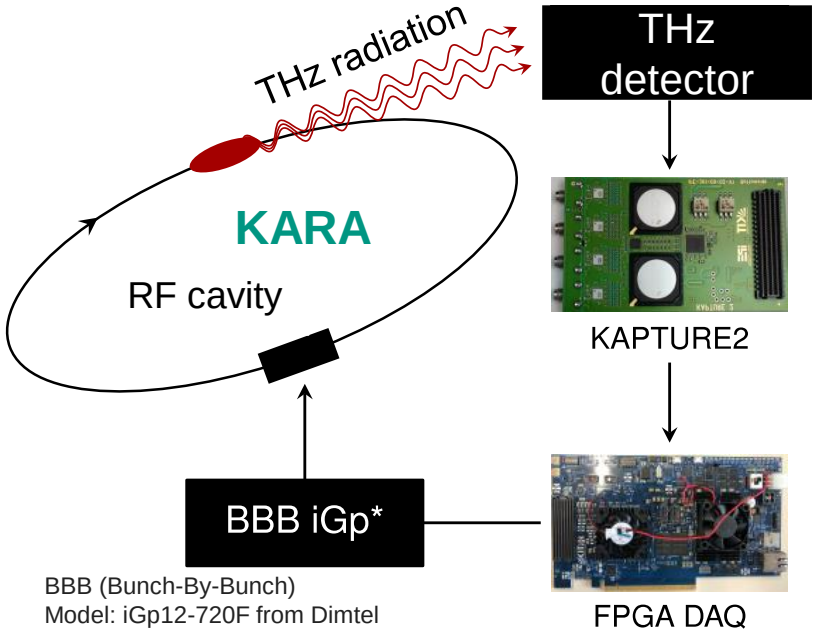
**KAPTURE board**

**Terahertz detector pulse**

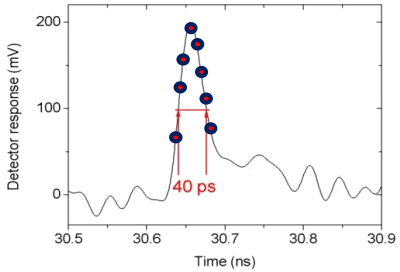



- Sampling time of 3 ps, local sampling frequency > 300 GS/s
- Up to 1 GHz pulse repetition rate
- Pulse amplitude (mV) and arrival time (ps) accuracy
- Real-time pulse sampling for long observation time
- Real-time FFT and measurement of CSR fluctuation by GPU

# Hardware Design of Feedback Loop




KAPTURE




- Sampling the CSR
- Extraction of the frequency of the instability

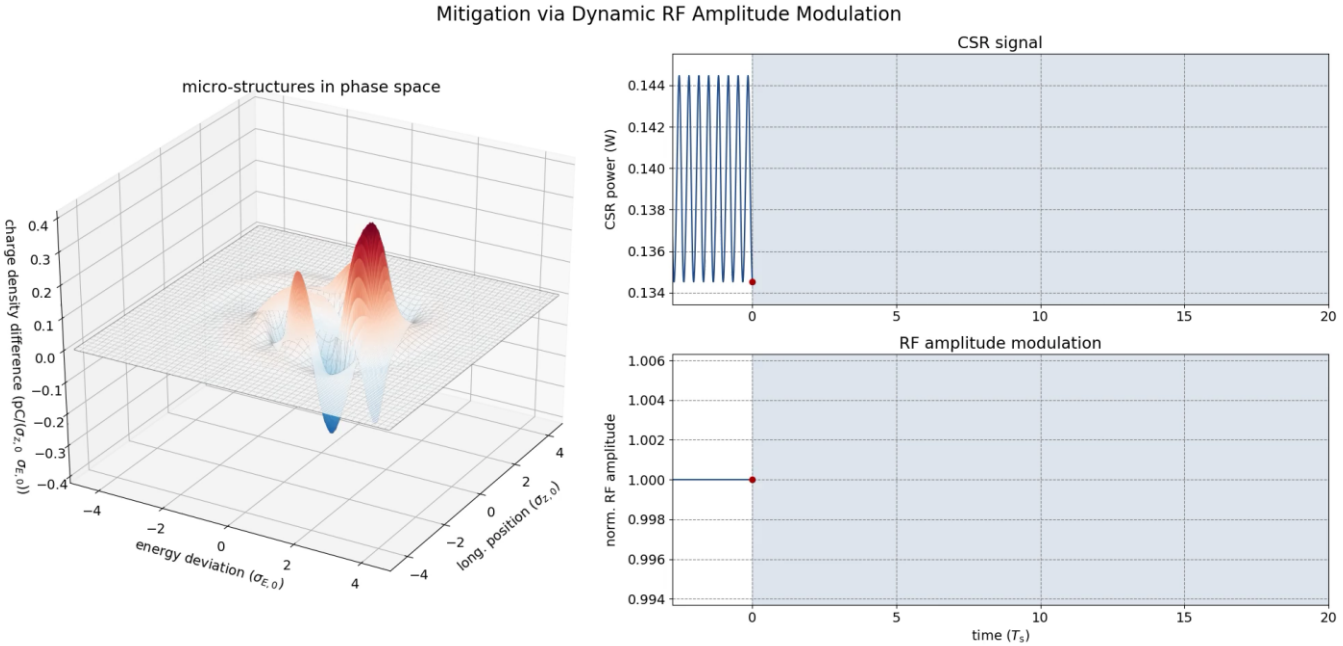
FPGA DAQ:

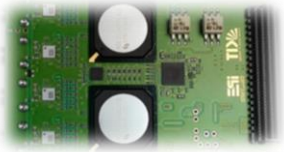
- Real-time process of CSR signal
- RL algorithm running on the FPGA receives the measurements of CSR and decides the action (RF modulation)

The action is processed and, by the Bunch-By-Bunch feedback system, sent to the kicker cavity

T. Boltz, W. Wang et al, Accelerating Machine Learning for Machine Physics (an AMALEA-project at KIT), ICALEPCS (2019), doi:10.18429/JACoW-ICALEPCS2019-TUCPL06

# Simulation of Feedback Control



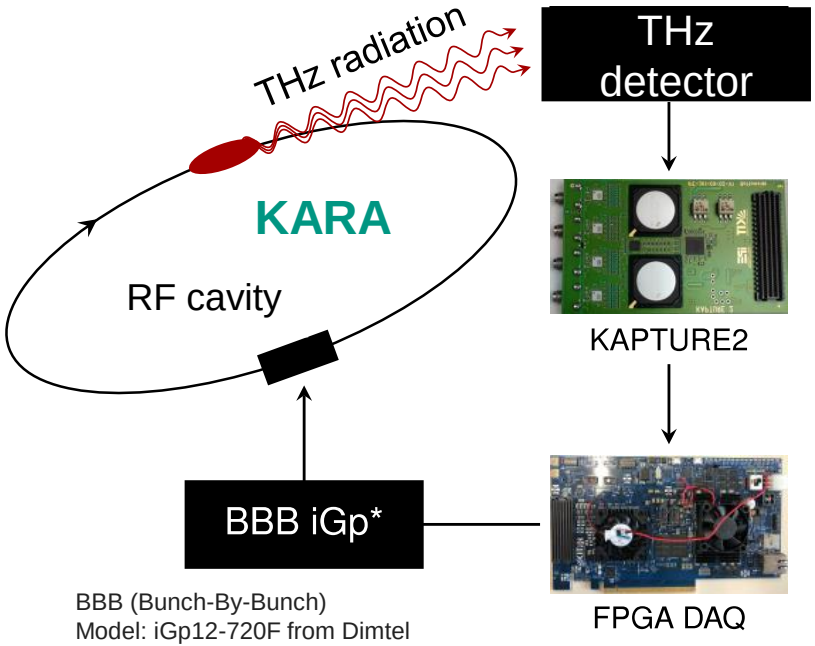



THz CSR acquired by KAPTURE

Example of RF cavity control (real-time)

→ To be implemented by AI

# Time Requirement




BBB (Bunch-By-Bunch)
Model: iGp12-720F from Dimtel

**Which Algorithm?**
**How to implement on Hardware?**

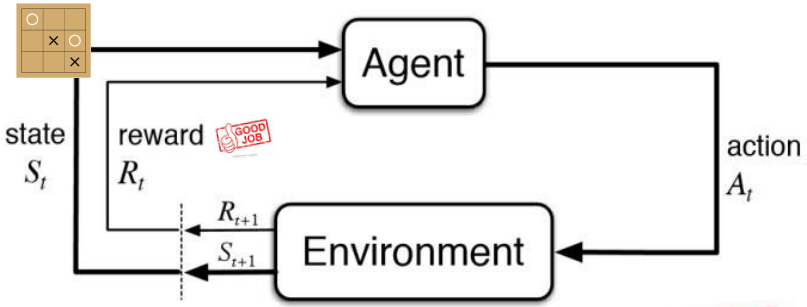
## Timing Contributions

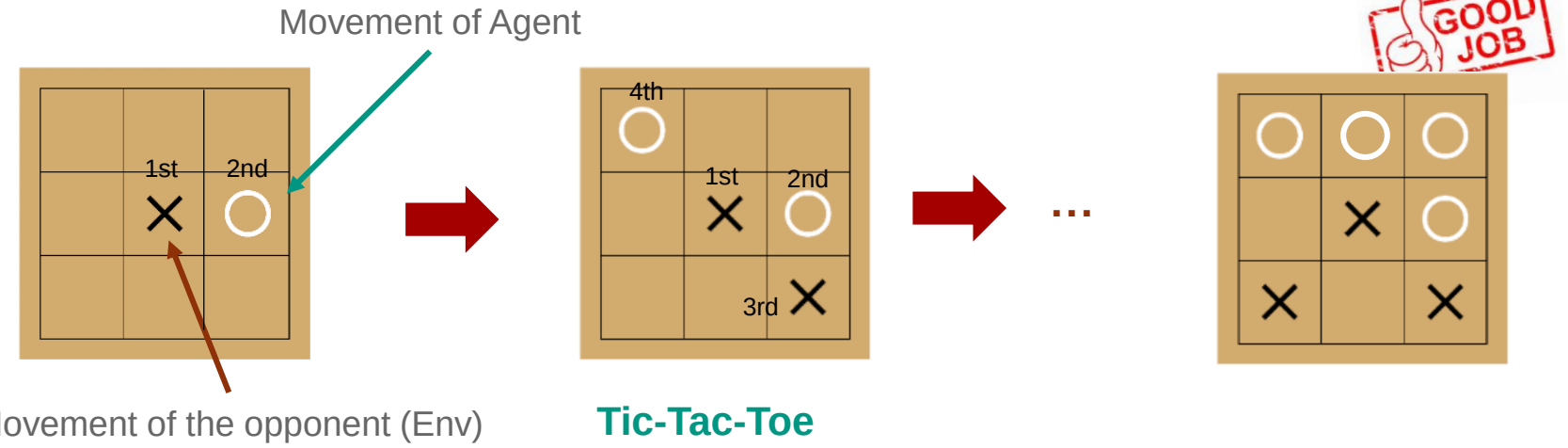
+ 1. THz detector/s
+ 2. Front-End Electronics
+ 3. Measurement of CSR signal (amplitude, time, frequency)
+ 4. Feature extraction from CSR
+ 5. Data processing based on AI processing
+ 6. Fast feedback to BBB

$$\sum_i t_i < \textbf{Hundreds of µs}$$

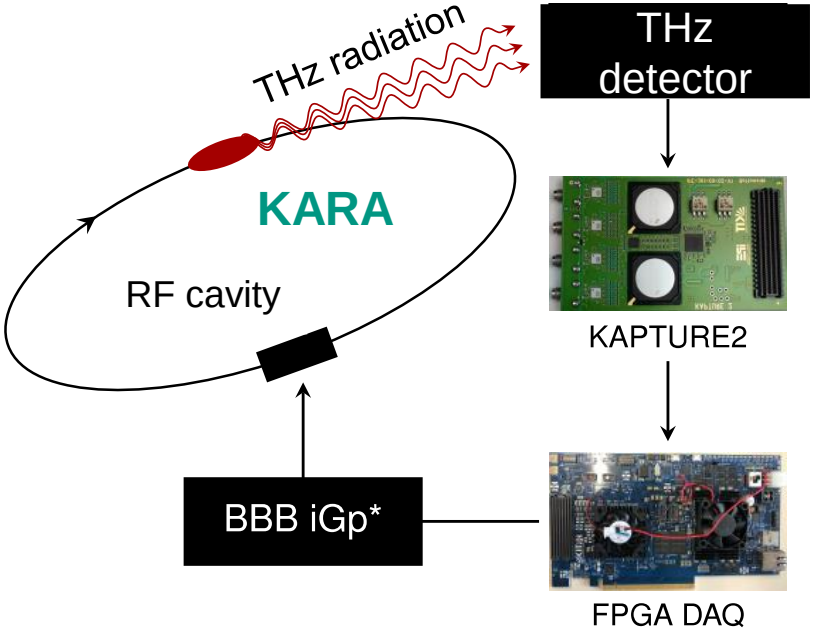
# The Reinforcement Learning Approach

- Goal-directed learning from interaction with an environment
- No pre-existing data set, trial-and-error learning → reinforce “good” behavior
- Markov Decision Process (MDP)



# Defining Reinforcement Learning




The action is processed and, by the Bunch-By-Bunch feedback system, sent to the kicker cavity

## Observable (state definition): CSR signal

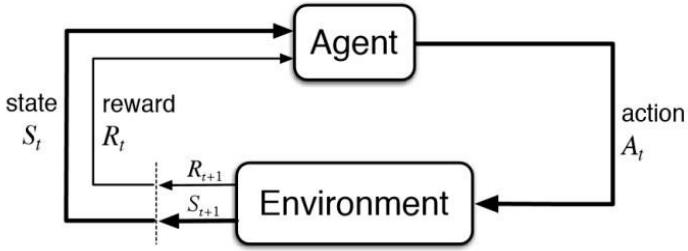
We can consistently and reliably measure the THz emission thanks to KAPTURE II. Provides information about the micro-bunching dynamics

## Theoretical observable (state definition): charge distribution

Ideal, we use it in simulations.
Vlasov-Fokker- Planck solver Inovesa

## Reward

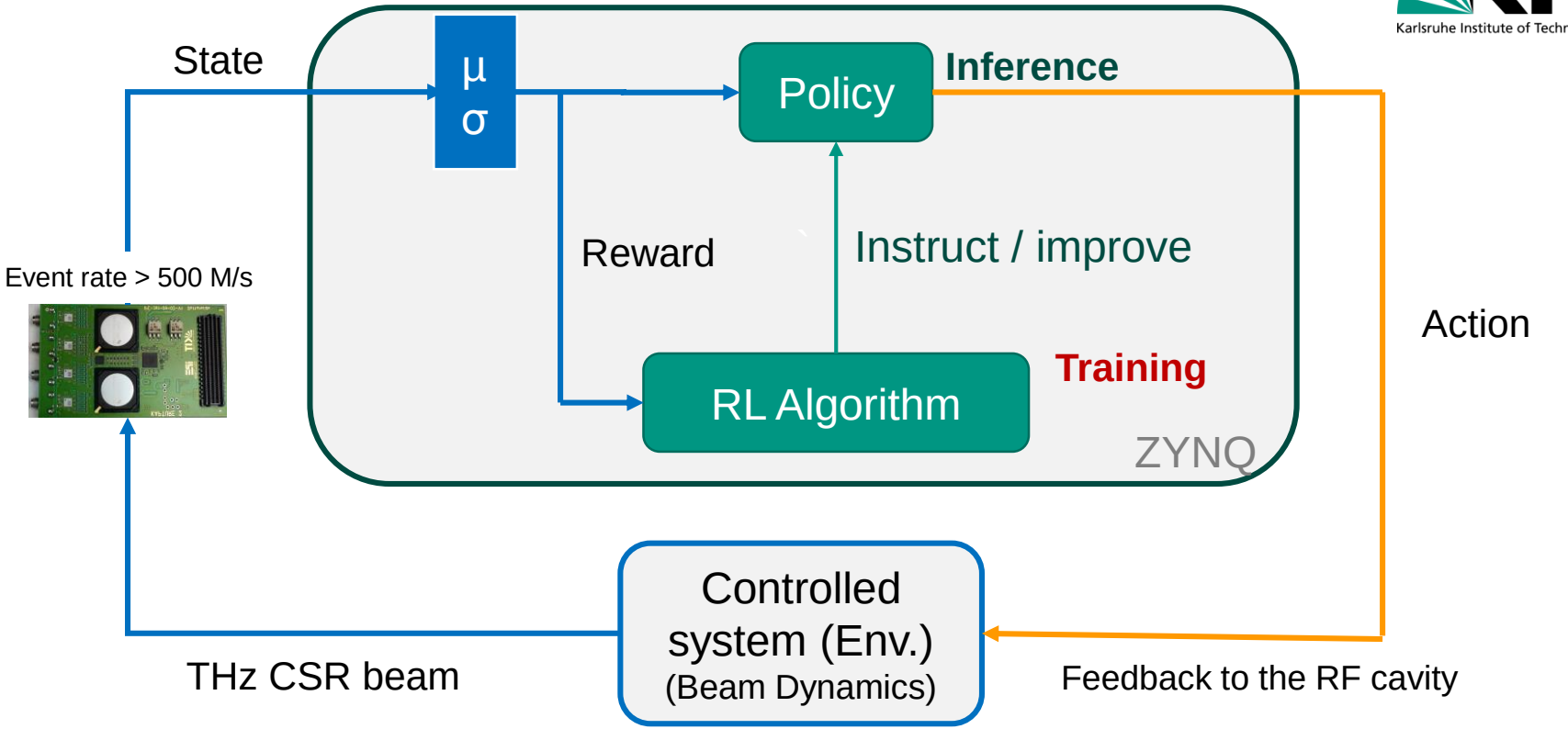
Based on average and STD



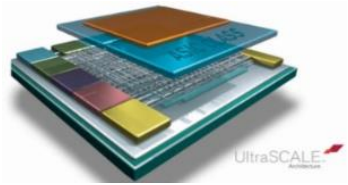

## Action

Modulation of the RF amplitude

# Hardware Deployment of RL Agent



# FPGA - AI platform: HighFlex 2




- Processor System (ARM): User Applications
- Programmable Logic (FPGA): fast and low latency application

Front-End:
KAPTURE
KALYPSO

- 12 lanes @ 28 Gbps
- Data throughput (full-diplex) up to 336 Gbps

- Compatible with standard FMC

PCI EXPRESS

- PCIe Gen 4 (x8 or 16 lanes)
- Data rate up to 240 Gbps

- Two SSD raid Local data storage

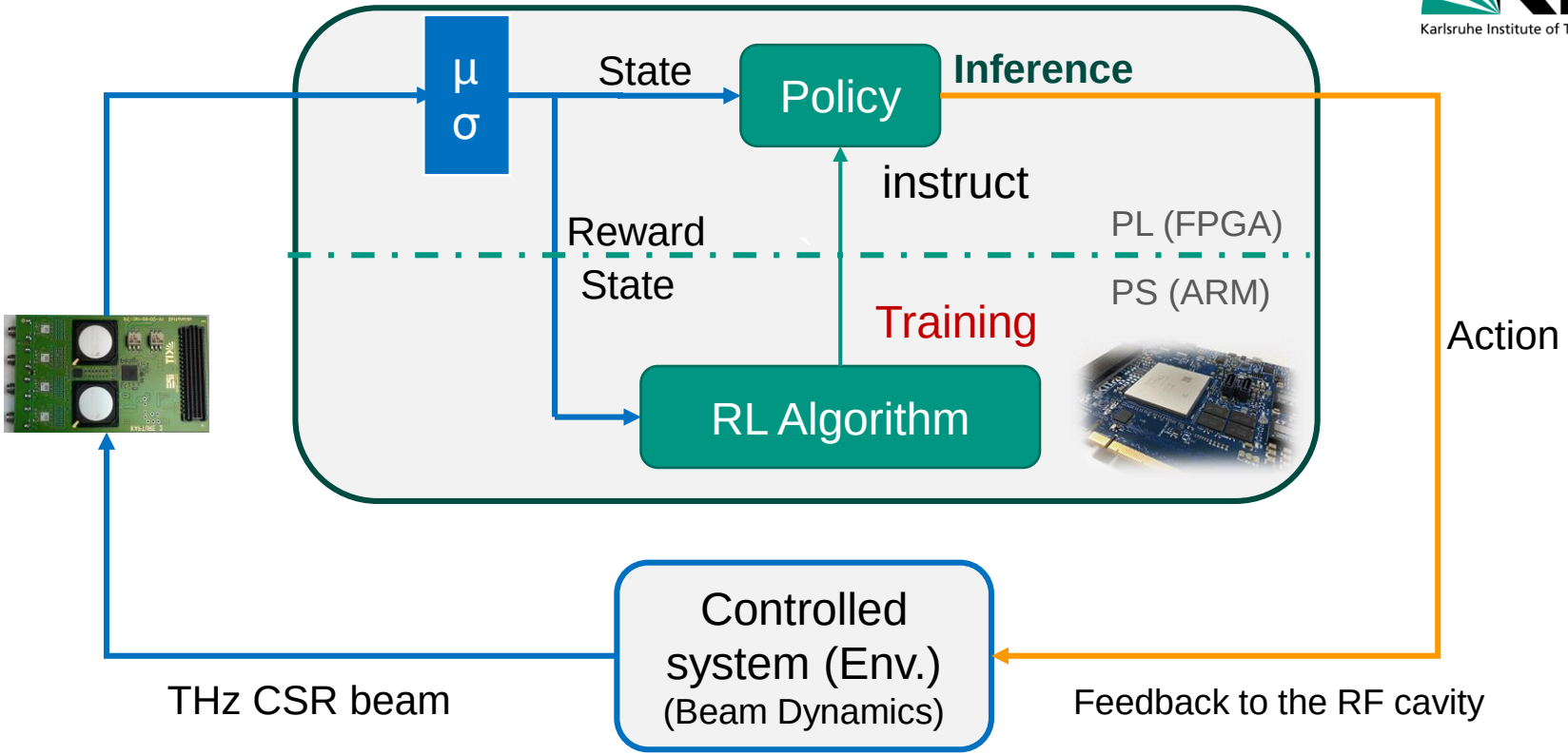
# HighFlex 2 FPGA: ZYNQ Ultrascale plus

- System Logic Cell: 653 K
- Flip-Flops: 597 K
- LUT: 298 K
- Distributed RAM: 9,1 Mb
- Block RAM: 21.1 Mb
- UltraRAM: 22.5 Mb
- DSP Slices: 2928
- PL-DDR4: 2 GB

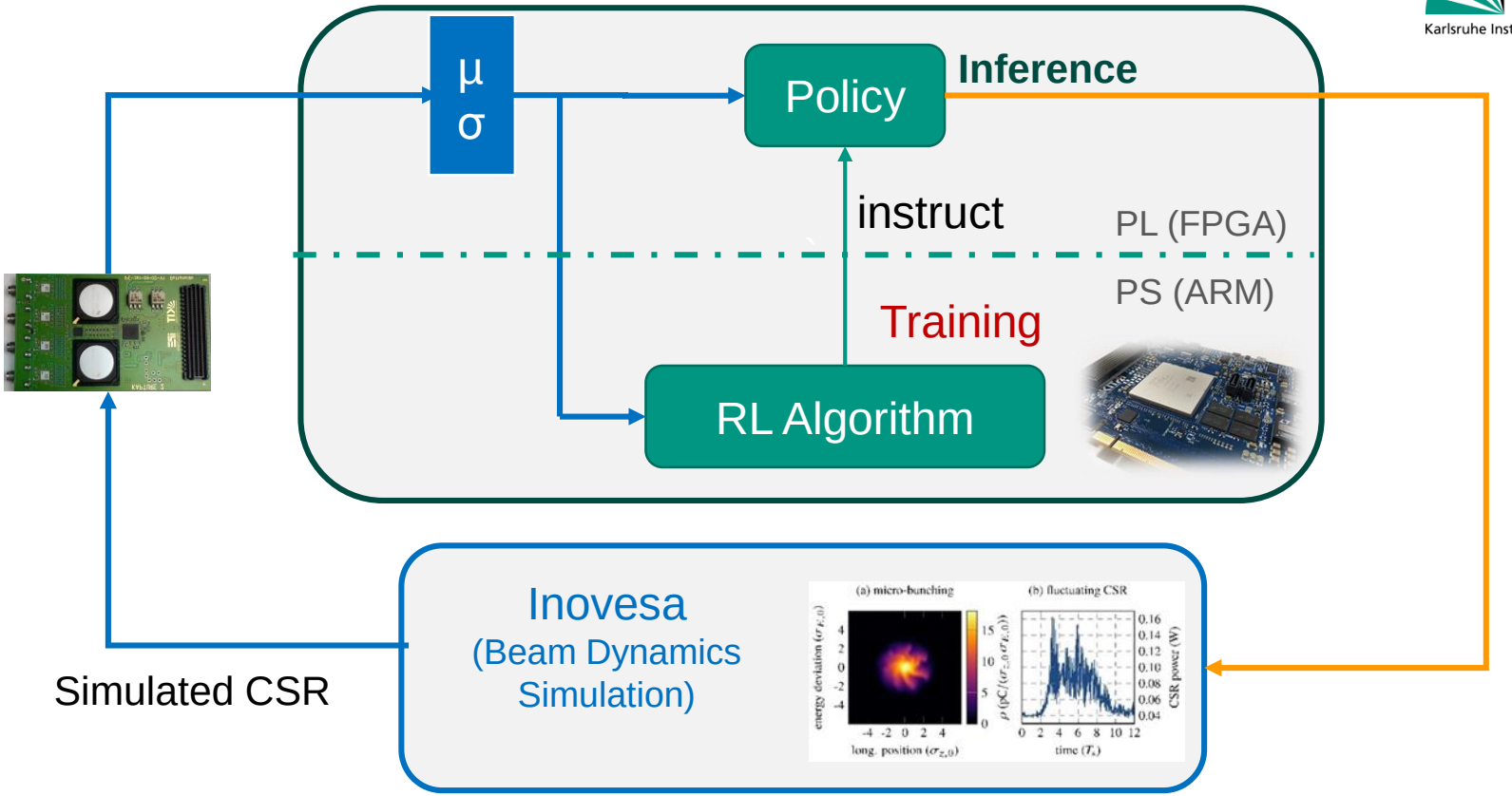
**AMBA AXI4 interfaces for primary data communication**

- Quad-core Arm Cortex-A53
- NEON & Single/Double Precision Floating
- PS-DDR4: 4 GB

# Hardware Deployment of RL Agent

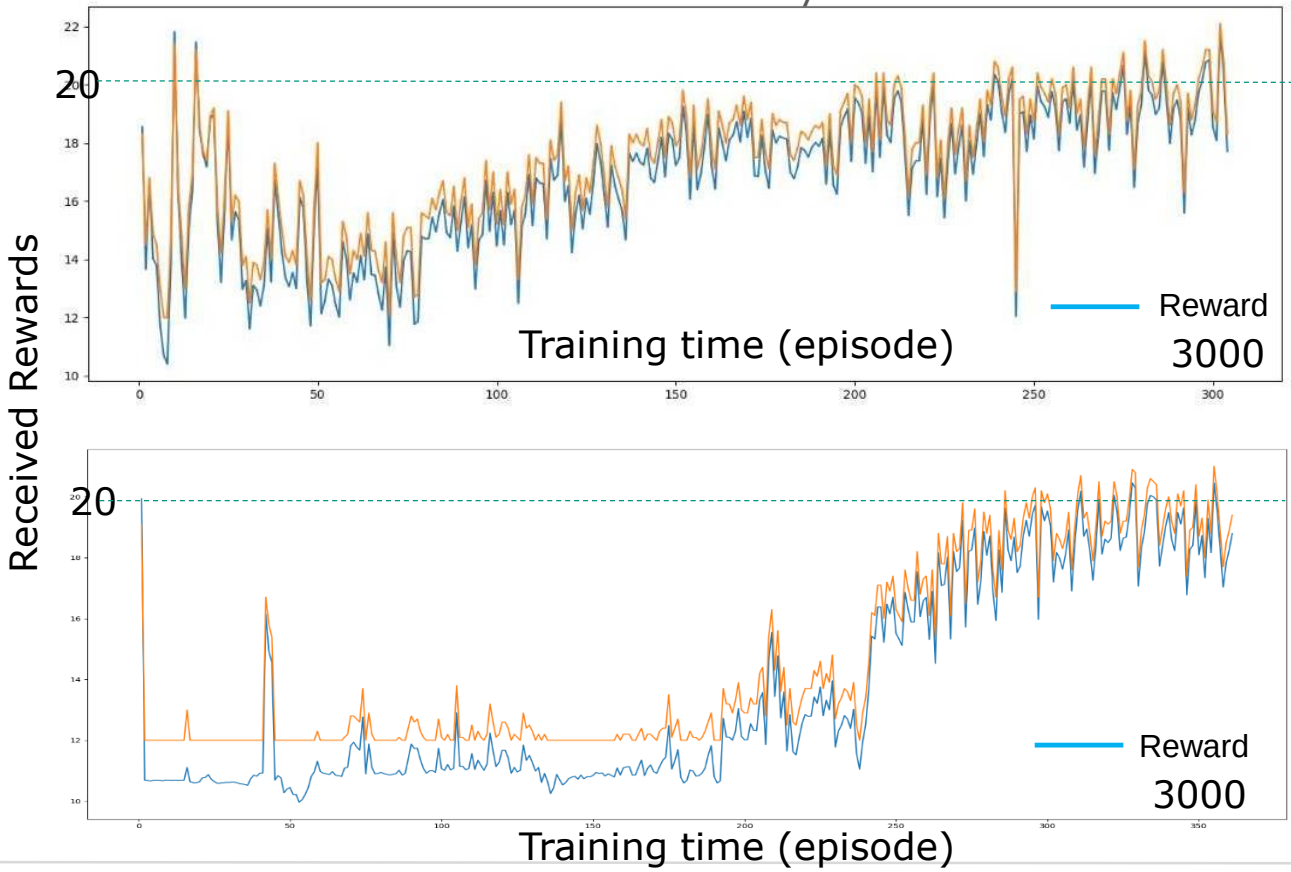


# Proof of Concept



# Comparison between FPGA and GPU (Keras-RL)

Simulation results by Inovesa



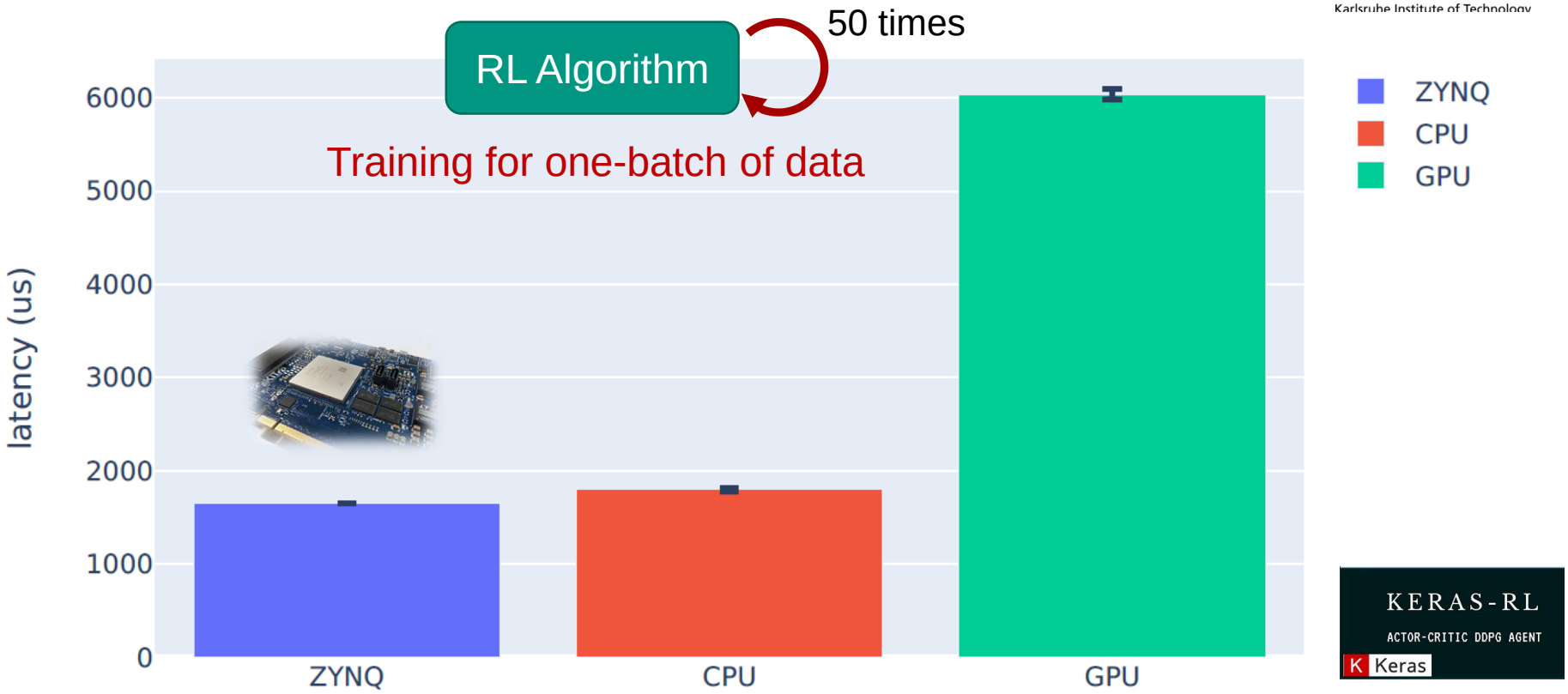
RL on FPGA

- Episode: agent behave badly and interaction stops
- The hardware achieve the similar learning curve compared to Keras-RL

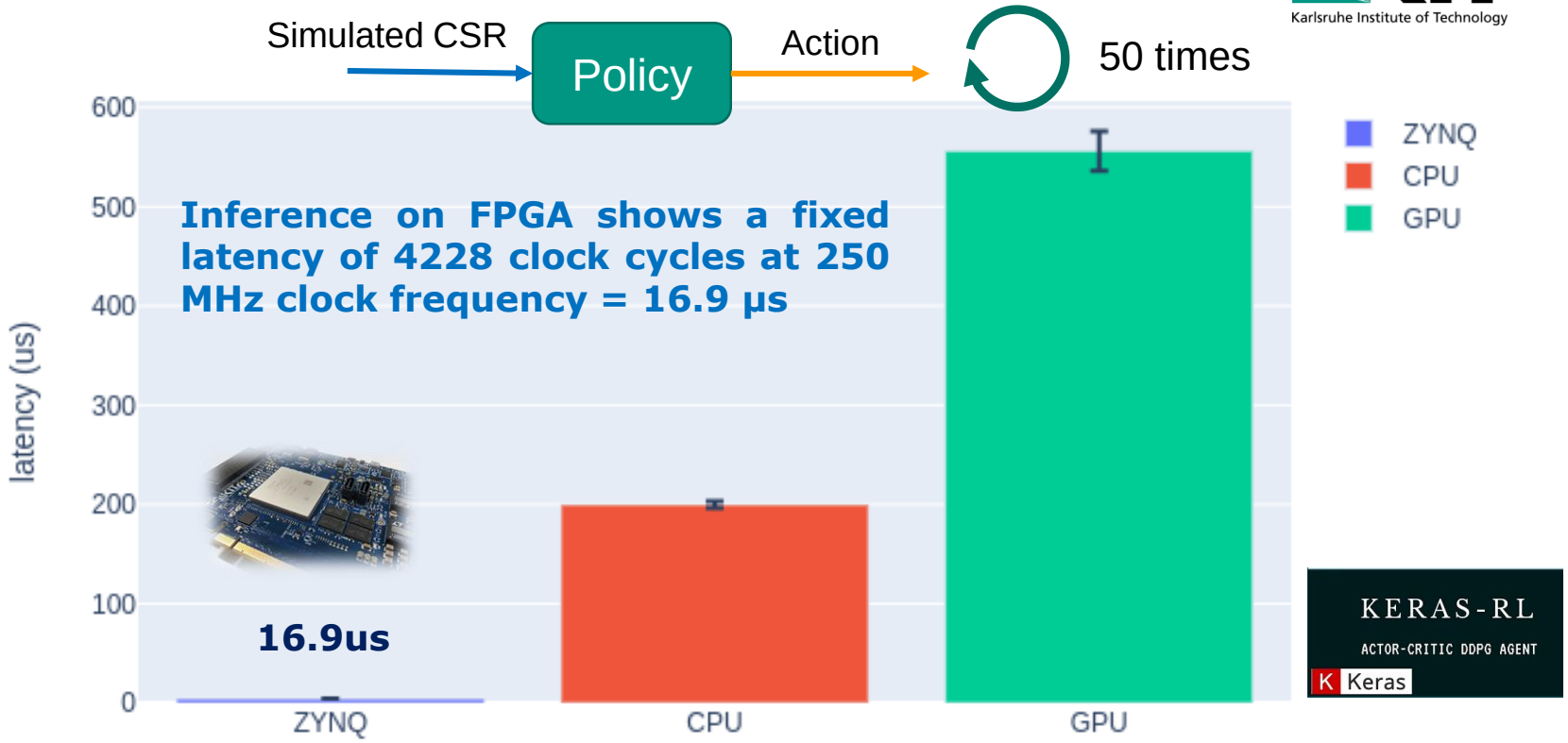
KERAS-RL
ACTOR-CRITIC DDPG AGENT
Keras

RL on GPU

# RL training performance



# RL inference performance



# Conclusion & what‘s next

- Microbunching instability study at KARA
- Fast detector and beam diagnostics fully developed
- Hardware implementation of the feedback loop control → tested

- Developed a framework for the implementation of an RL algorithm on ZYNQ-FPGA
- Preiminary results show a high inference performance of about 17 µs
- Training performance in the order of > 1 ms, *to be improved*

*What’s next*

- Test the feedback system including the RL at KARA
- Further investigation of potential support of different RL algorithms
- Further investigation of different FPGA and strategies to reduce the training time

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# Thank you for your attention

# Backup Slides

# Applying Reinforcement Learning to our case

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## Observable (state definition): CSR signal

We can consistently and reliably measure the THz emission thanks to KAPTURE II. Provides information about the micro-bunching dynamics

## Theoretical observable (state definition): charge distribution

Ideal, we use it in simulations.

Difficult to integrate in our feedback loop?

## Action

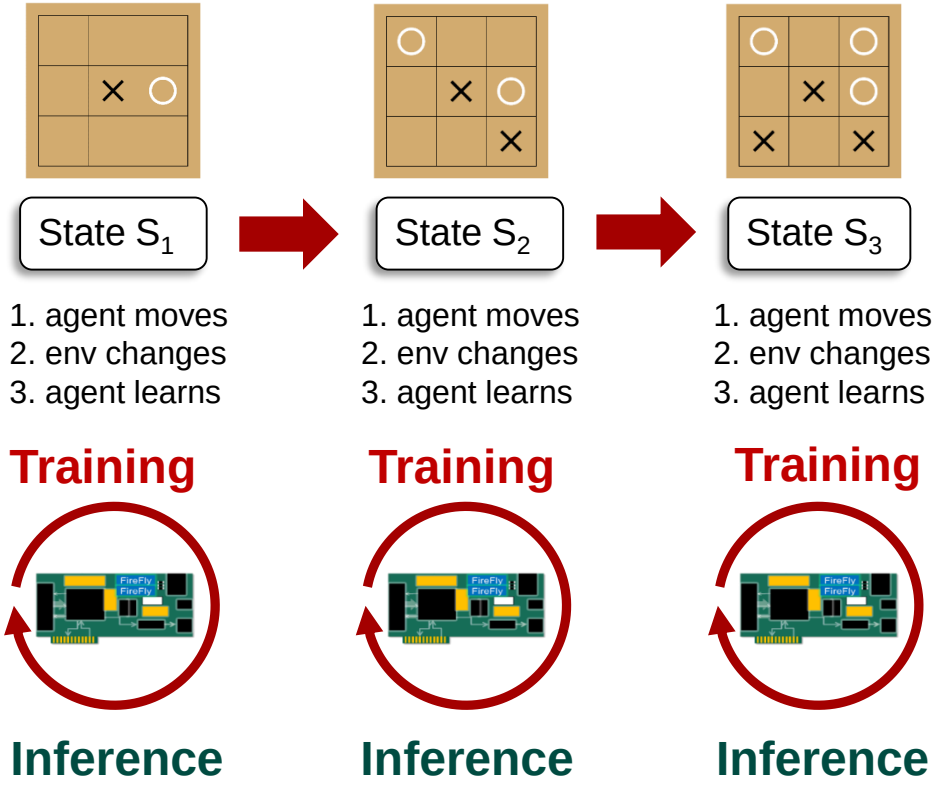
Modulation of the RF amplitude

## Reward

R = $\mu_{CSR} - w\,\sigma_{CSR}$ where $w$ is a weight

Could we improve the reward definition?

# Hardware Requirement of Reinforcement Learning




## Online Training

Each step involves training and inference!

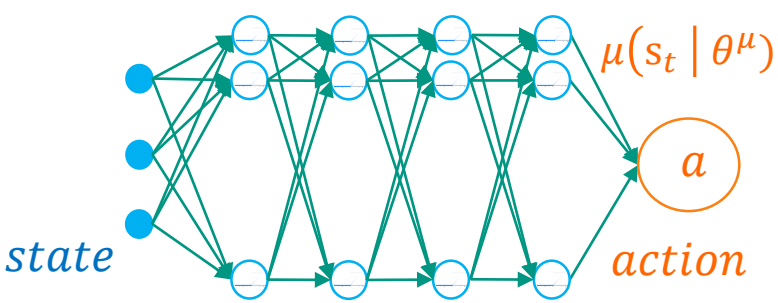
$$\sum_i t_i <$$

**Hundred of µs**

+ 3. Collect and interpret the CSR signal
+ 4. Transfer the control to BBB
+ 5. Generate the control signal
+ 6. Collecting training data
+ 7. Backward propagation
+ 8. Updating networks

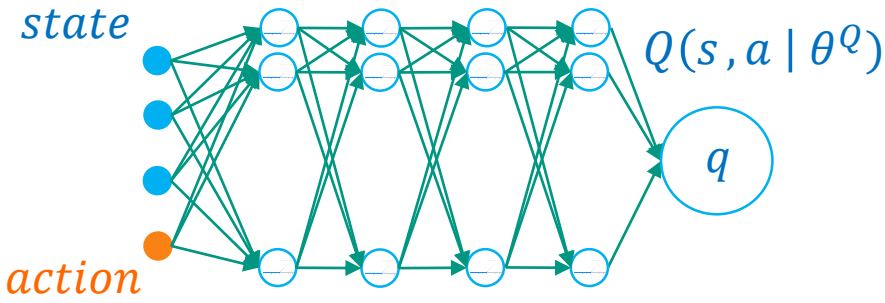
# Deep Deterministic Policy Gradient

Actor Network (Policy)




- Actor is component that learns policies
- Actor follows the instruction coming from the Critic Network, in practice, it update towards a direction that maximum the q value.

Critic Network (Value)

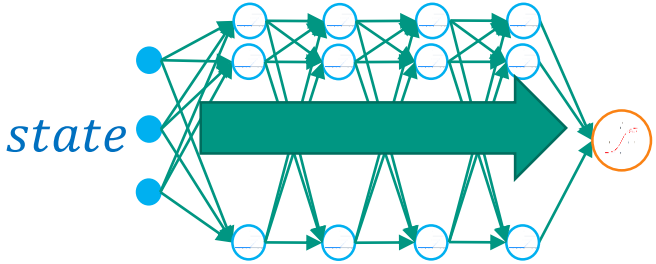



- Critic learns the state-value function that used for “criticize” the actor’s policy.
- Critic update through the TD errors, in practice, it is updated by the reward signal collected from the environment

# Hardware Implementation of DDPG

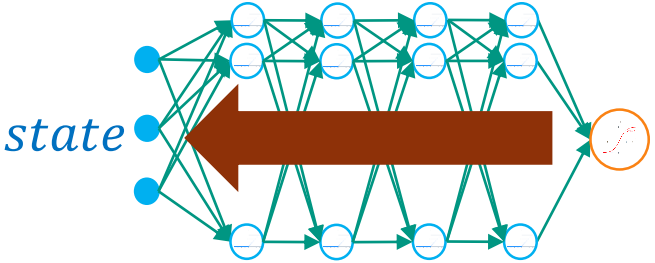
Actor Network (Policy)
Inference

$$\mu(s_t \mid \theta^{\mu}) = action$$




- Actor is used for generate action signal
- This needs a relatively easy calculation and fixed-point value can fulfill the requirement.

Actor Network (Policy)
Training




- Actor network training use the information from critic network for a backpropagation.
- This needs a relatively complex calculation and floating point value.