



# Real-time Reinforcement Learning on FPGA with Online Training for Autonomous Accelerators

Luca Scomparin, Jürgen Becker, Edmund Blomley, Erik Bründermann, Michele Caselle, Timo Dritschler, Andreas Kopmann, Anke-Susanne Müller, Andrea Santamaria Garcia, Johannes L. Steinmann, Chenran Xu | 5-8 March 2024



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Introduction & Motivation	FPGAs and more	Betatron oscillations	Microbunching instability	$\underset{\circ}{\text{Conclusion}}$
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Microbunching instability

 $\underset{\circ}{\text{Conclusion}}$ 

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#### Usually data-hungry



Microbunching instability 000000

Conclusion





### Usually data-hungry

#### Great data rate $\rightarrow$ lot of training data







Usually data-hungry

Great data rate  $\rightarrow$  lot of training data

Possibility of training online

Microbunching instability

Conclusion





Usually data-hungry

Great data rate  $\rightarrow$  lot of training data

Possibility of training online

No simulation required!



Betatron oscillations

Microbunching instability

Conclusion

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Usually data-hungry

Great data rate  $\rightarrow$  lot of training data

Possibility of training online

No simulation required!

### Timing constrains become relevant!

Betatron oscillations

Microbunching instability

Conclusion

### What is Real-Time?



Shin and Ramanathan (1994) identify major components:

Correctness of a computation depends not only on the logical correctness but also on the time at which the results are produced.

- "time" is the most precious resource;
- reliability is crucial;
- environment of operation is an active component.

Predictability is fundamental!

Three possible levels/categories:

- hard, catastrophic consequences;
- *firm*, results produced late not useful;
- soft, later means decreasing usefulness.

Depending on environment, RL can be either one of these!

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#### Case study: KARA



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Example signal



Synchrotron frequency/period  $O(10 \, \text{kHz} \leftrightarrow 100 \, \mu \text{s})$ 

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Huge variety of time scales!

### **Issues of Real-Time AI**

- Current ML frameworks have mainly throughput in mind → no/little real-time optimization;
- use of batched execution on GPU  $\rightarrow$  not optimal for latency;
- conventional computing hardware not meant for low-latency real-time;
- it still works great for latency in the millisecond range!



**FPGAs** and more

Introduction & Motivation

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# Heterogeneous platforms

Different computing platforms  $\rightarrow$  different benefits

Heterogeneous combine CPUs, FPGAs and "GPUs"

An example, AMD Versal:

- combines FPGAs and ARM CPUs;
- AI Engine array for heavy multiplication workloads;
- Network-on-Chip interconnect;
- high-speed interfaces.

Introduction & Motivation

# These computation unit work in synergy and share memory!



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FPGAs and more

#### The KINGFISHER RL platform



Experience accumulator

Real-Time inference BUT Offline/Batched training

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### The KINGFISHER RL platform

#### Experience accumulator

Real-Time inference BUT Offline/Batched training

Pros:

- + "easy" real-time;
- + can use complex training algorithms;
- + can use GPUs and other accelerators;
- + training time reward definition<sup>™</sup>.

Cons:

- data inefficient;
- actor design is critical;
- training overhead.











# Idea Start simple $\rightarrow$ test all components together

- Betatron oscillations ( $\approx$  700 kHz)are well understood
- Easy to frame as Markov Decision Process
- Classical control for comparison

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#### First test: betatron oscillations

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Excite oscillation with kicker, damp it with RL!





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Step 99

Reward with L1 norm, L2 norm and tanh. 2.7 MHz action rate!









Unstable coherent synchrotron radition (THz) production

- Self-interaction of bunch with emitted radiation
- Nonlinear dynamics, several timescales/frequency components
- Main timescales:  $O(10 \,\mu s)$ ,  $O(10 \,m s)$ , with  $T_s = O(100 \,\mu s)$
- Expensive to simulate!

Longitudinal momentum



# Introduction & Motivation co



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### Perfect candidate for real time RL!

























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### **RL** problem definition

Environment  $\rightarrow x_i$  Coherent Sychrotron Radiation power each turn

#### **Initial approach**

 $\mathbf{O} = \{\mu_{\text{CSR}}, \sigma_{\text{CSR}}, \mathbf{\textit{m}}_{\text{trend}}, \mathbf{\textit{A}}_{\text{FFT max}}, \mathbf{\textit{f}}_{\text{FFT max}}, \Delta_{\theta}\}$ 

 $A = \{A_{mod}, f_{mod}\}$ 

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#### New approach

 $y_i = \{$ filtered and decimated  $x_i \}$ 

 $O = \{N \text{ latest } x_i\}$ 

A = action or delta-action

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#### Reward is observation based and varies at runtime

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- 64 samples input into network
- Sampling rate affects network time-span
- Filter signal → remove high-frequency components
- Drop samples  $\rightarrow$  network "sees" more time





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#### Possibility of cumulative action



#### System schematic







#### In action



Reward with L2 norm from average

### Conclusion

- First online training purely on accelerator
- µs Real-Time RL is a viable option
- Its performance is problem dependent
- FPGAs and Heterogeneous platforms are the key
- Hardware aware problem design is fundamental



AlexBlechman

Programming is chaotic magic. There are no rules. You ask a game dev "Can the player summon a giant demon that bursts from the ground in an explosion of lava?" and they'll say "sure, that's easy" and then you'll ask "can the player wear a scarf?" and they'll go "oof"

#### Sounds interesting? Let's find more applications!

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