

Feedback Design for Control of the Micro-Bunching Instability based on Reinforcement Learning

Tobias Boltz, Miriam Brosi, Erik Bründermann, Bastian Härer, Peter Kaiser, Christoph Pohl, Patrick Schreiber, Minjie Yan, Tamim Asfour and Anke-Susanne Müller | June 24, 2019

Laboratory for Applications of Synchrotron Radiation (LAS)







www.kit.edu

Micro-Bunching and CSR Power Fluctuations micro-structure dynamics 0.16 4 15 0.14 ο (pC/(σ_{z,0} σ_{E,0})) CSR power (W energy $(\sigma_{E,0})$ 2 0.12 10 0 0.10 0.08 -2 5 0.06 -4 0.04 -4 -2 2 4 2 10 12 0 6 8 long. position ($\sigma_{z,0}$) time (T_s)

 \Rightarrow continuous variation of charge distribution leads to fluctuating CSR

Micro-Bunching Instability

Micro-Bunching Instability



CSR self-interaction



Micro-Bunching Instability



CSR Power Spectrogram: Dependency on Bunch Current



Simulation code: Parallelized VFP solver *Inovesa* (https://github.com/Inovesa/Inovesa) Schönfeldt, P. *et al.*, Phys. Rev. Accel. Beams 20 (2017)

Reinforcement Learning



... in a Nutshell: Learning from Interaction

- goal-directed learning from interaction (trial-and-error search)
- mathematical foundation: Markov decision process (MDP)
 "The future is independent of the past given the present."



Reinforcement Learning



... in a Nutshell: Finding better Policies

- value function q_{π} is the expected cumulative reward following policy π
- general policy iteration (GPI)
 - policy evaluation: learning the value function
 - policy improvement: exploiting the gained knowledge



Figure: adapted from Reinforcement Learning, Sutton, R.S. and Barto, A.G., 2nd edition, MIT Press (November 2018)

Reinforcement Learning



... in a Nutshell: Actor-Critic System using NNs



*Continuous control with deep reinforcement learning, Lillicrap, T.P. et al. (2015), https://arxiv.org/abs/1509.02971



Definition of Partially Observable MDP



THz diagnostics (KAPTURE) and RF system at KARA



Observation, Reward and Action

- observation: hidden state of electron bunch • $\mathbf{o} = (\mu, \sigma, m, f_{\text{max}}, A_{\text{max}}, \varphi_{\text{max}})^{\mathsf{T}} \Rightarrow \text{full CSR signal or phase space?}$
- reward function: optimization of emitted CSR signal $R = w_1 \mu w_2 \sigma$ with $w_1, w_2 > 0 \Rightarrow$ best ratio w_1/w_2 ?
- action: modifications to the RF system
 - 1) scale RF amplitude and phase:
 - $\mathbf{a} = (V_{\mathsf{RF}}, \varphi_{\mathsf{RF}})^{\mathsf{T}}$
 - 2) restrict to modulations of V_{RF} and φ_{RF} : $\mathbf{a} = (A_V, f_V, A_{\varphi}, f_{\varphi})^{\text{T}}$





Observation, Reward and Action

- observation: hidden state of electron bunch • $\mathbf{o} = (\mu, \sigma, m, f_{\max}, A_{\max}, \varphi_{\max})^{\mathsf{T}} \Rightarrow \text{full CSR signal or phase space?}$
- reward function: optimization of emitted CSR signal $R = w_1 \mu w_2 \sigma$ with $w_1, w_2 > 0 \Rightarrow$ best ratio w_1/w_2 ?
- action: modifications to the RF system
 - 1) scale RF amplitude and phase: $\mathbf{a} = (V_{\text{BF}}, \varphi_{\text{BF}})^{\text{T}}$
 - 2) restrict to modulations of V_{RF} and φ_{RF} : $\mathbf{a} = (A_V, f_V, A_{\varphi}, f_{\varphi})^{\text{T}}$





Observation, Reward and Action

- observation: hidden state of electron bunch • $\mathbf{o} = (\mu, \sigma, m, f_{\text{max}}, A_{\text{max}}, \varphi_{\text{max}})^{\mathsf{T}} \Rightarrow \text{full CSR signal or phase space?}$
- reward function: optimization of emitted CSR signal $R = w_1 \mu w_2 \sigma$ with $w_1, w_2 > 0 \Rightarrow$ best ratio w_1/w_2 ?
- action: modifications to the RF system
 - 1) scale RF amplitude and phase: $\mathbf{a} = (V_{\text{BF}}, \varphi_{\text{BF}})^{\text{T}}$
 - 2) restrict to modulations of V_{RF} and φ_{RF} : $\mathbf{a} = (A_V, f_V, A_{\varphi}, f_{\varphi})^{\text{T}}$





Tools and Packages

- simulation code Inovesa is written in C++, everything else in Python
- (mainly) used Python packages:



- (so far) testing and prototyping is done on standard Desktop PC
- ideas towards implementation include FPGA and GPU systems (cooperation with IPE)



First Results using the DDPG Algorithm





First Results using the DDPG Algorithm





First Results using the DDPG Algorithm



Summary and Outlook



Open Questions

early results indicate stationary optimization might be sufficient,
 i.e. finding and repeating the best action (*multi-armed bandit problem*)

however, ...

- action is expected to depend on the state (CSR self-interaction)
- different bunch currents, machine settings and reward functions need to be explored ⇒ is control possible with a singular agent?
- what happens in a noisy environment, i.e. the real accelerator?
- definition of observation / state (retaining the Markov property)
- choice of action space \Rightarrow what influences the micro-bunching?
- transferability to different control tasks / instabilities?



Thank you for your attention!

Backup

Markov Property and Phase Space

- Markov property in Inovesa: configuration parameters and initial phase space density determine results (*true state*)
- not just a feature of VFP solvers, but something that's rooted in the definition of phase spaces

phase space density





Backup



Effects of RF Amplitude Modulation ($A_V = 0.2 V_0$, $f_V = 4.78 f_s$)



Backup

Effects of RF Amplitude Modulation ($A_V = 0.2 V_0$, $f_V = 5 f_s$)

