## Neuromorphic Controls: From the dynamics of a cartpole to a lunar lander

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| Introduction |
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| - Neuromorphic architecture: A promising candidate for non von- |
| Neumann computation |
| Qse of spikes trains (impulses distributed spatio-temporally) for |
| processing as opposed to continuous time signals. |
| Low power computation with spiking neural networks(SNNs) for |
| AI. |
| Q SNNs for optimal and data-driven control: Application to cartpole |
| balancing and soft landing of a lunar lander. |



## Aim: The Research Question

Can SNNs provide acceptable performance for applications in conventional optimal and data-driven control techniques?

$\square$ Python based simulation models for both cartpole and lunarlanders
$\square$ For the cartpole balancing, standard linear quadratic regulator (LQR) is used but with a single spiking neuron as a feedback matrix multiplier.
$\square$ For the lunar lander soft landing, deep Q learning (a version of reinforcement learning was used) with conventional artificial neural networks (ANNs) and SNNs to train the lander to execute soft landing on the given target area.


Control objective: To balance the pole on the cart for small perturbations about the unstable equilibrium position (UEP)

Achieved: Successful balancing with 1 spiking neuron based LQR feedback controller.

Control objective: To execute soft landing between the flags using three thrusters: left, right and main.

Achieved: Successful landing using Q learning and conventional non-spiking ANNs.

In progress: Learning to land using SNN based Q learning .

$\square$ A single spiking neuron can provide acceptable transient and steady state characteristics for feedback control.
$\square$ Implementing both the problems on a neuromorphic hardware can be the next step, to check for power benefits. $\qquad$

[1] Dingkun et al.,IEEE Tans. Ind. Ele 10.1109/TIE.2021.3095788 (2021) [2] Chen et al., Springerlink Machine
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