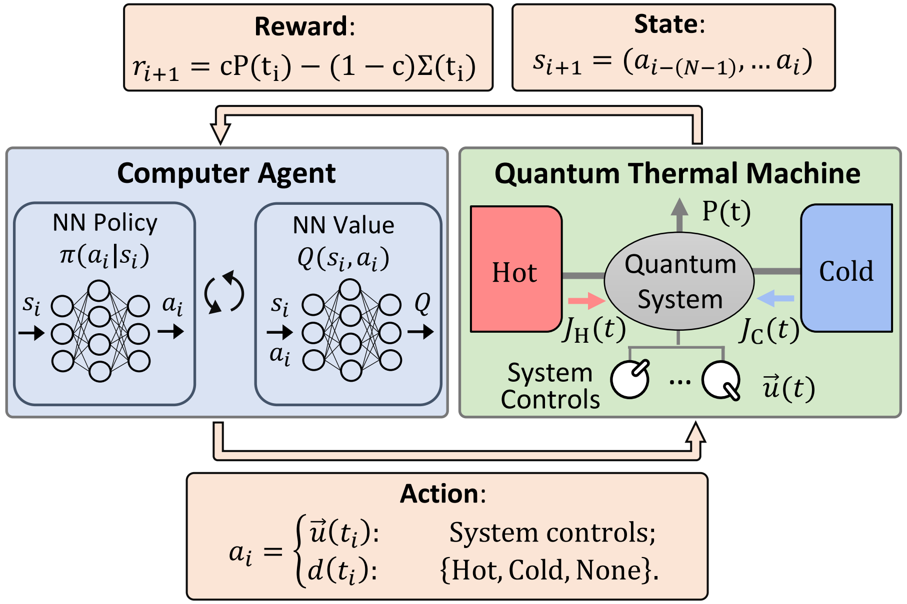
Driving black-box quantum thermal machines with optimal power/efficiency trade-offs using reinforcement learning

Driven Quantum Thermal Machine (QTM)



Goal

The goal is to determine the optimal cycles $\vec{u}(t), d(t)$ that maximizes the power - efficiency tradeoff

$$\langle r_c \rangle = c\langle P \rangle - (1-c)\langle \Sigma \rangle$$

where c ∈ [0,1].

Common approaches and assumptions

1) Optimize fixed cycle structure (Otto, Carnot, etc),
2) Speed up quasi-static cycles (i.e. using Shortcuts to Adiabaticity),
3) Optimize in slow/fast driving regime,
4) Variational approaches (i.e. Pontryaghin Minimum Priciple).

P.A. Erdman and F. Noé, NPJ Quant. Inf. 8, 1 (2022)

P.A. Erdman and F. Noé, arXiv:2204.04785 (2022)

Blackbox Reinforcement Learning (RL)

No information about cycle shape, nor model

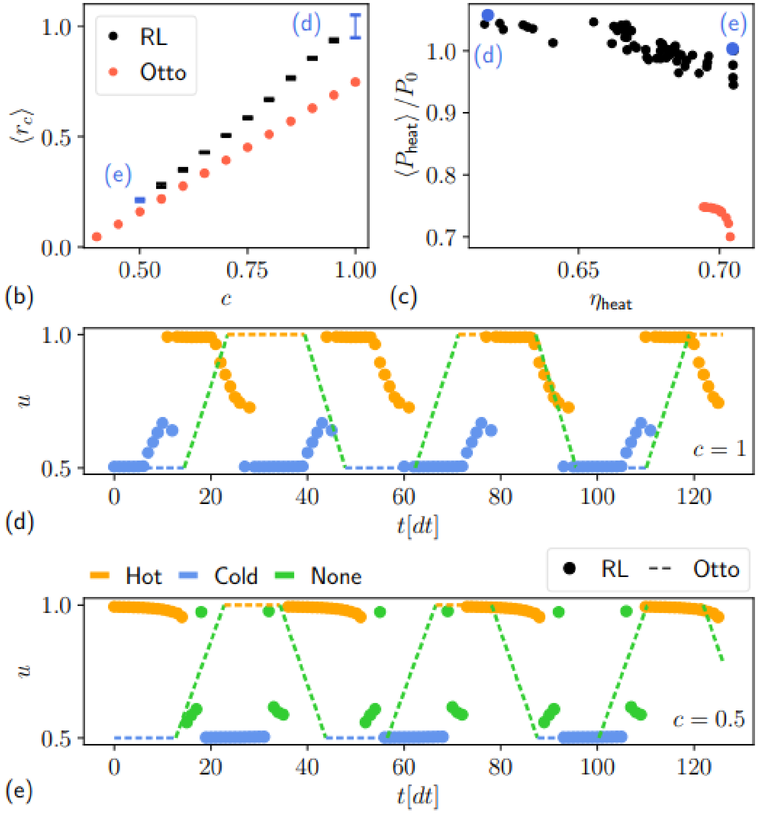
Only assumptions:

- We can observe the heat currents $J(t)$
- $J(t)$ depends on $\vec{u}(t), d(t)$ for $t \in [t, t-\tau]$

[T. Haarnoja et al., arXiv:1812.05905 (2018)]

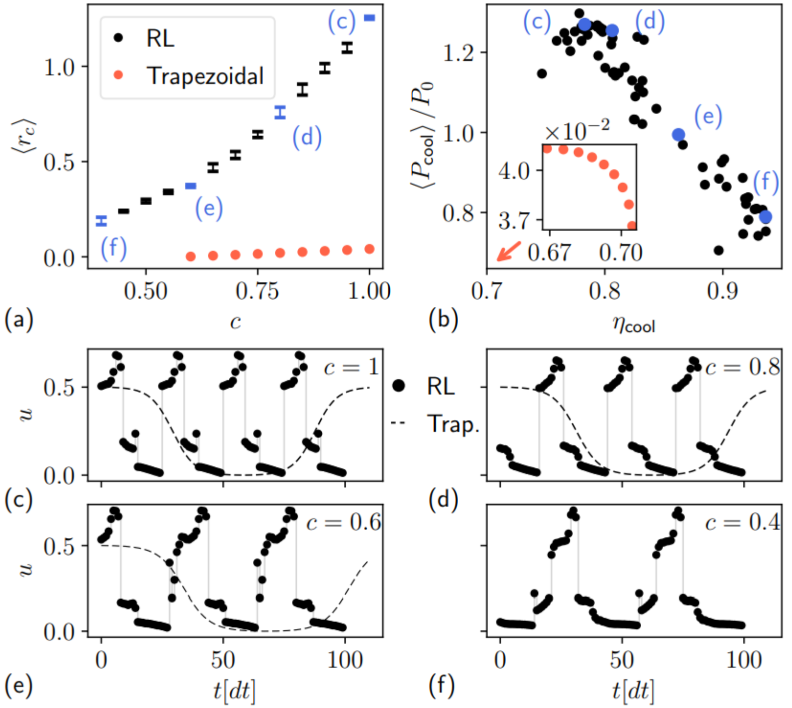
Results

Quantum Harmonic Oscillator heat engine: $\omega(t) = w_0 u(t)$



[Y. Rezek and R. Kosloff, New J. Phys. 8, 83 (2006).]

Qubit-based refrigerator: $H_{u(t)} = -E_0[\Delta\sigma_x + u(t)\sigma_z]$



[B. Karimi, J.P. Pekola, Phys. Rev. B 94, 184503 (2016)]

Future direction

- Optimize the power - efficiency - power fluctuations tradeoff
  $$\langle r_c \rangle = a\langle P \rangle - b\langle \Sigma \rangle - c\langle \Delta P \rangle,$$
  Where $a + b + c = 1$.
- Compare results with TUR and analytics in slow/fast driving.
- Find full Pareto front with $\langle P \rangle$, η, $\langle \Delta P \rangle$.

[P.A. Erdman, A. Rolandi, P. Abiuso, F. Noé, and M. Perarnau-Llobet, in preparation]