Battery Model Calibration with Deep Reinforcement Learning

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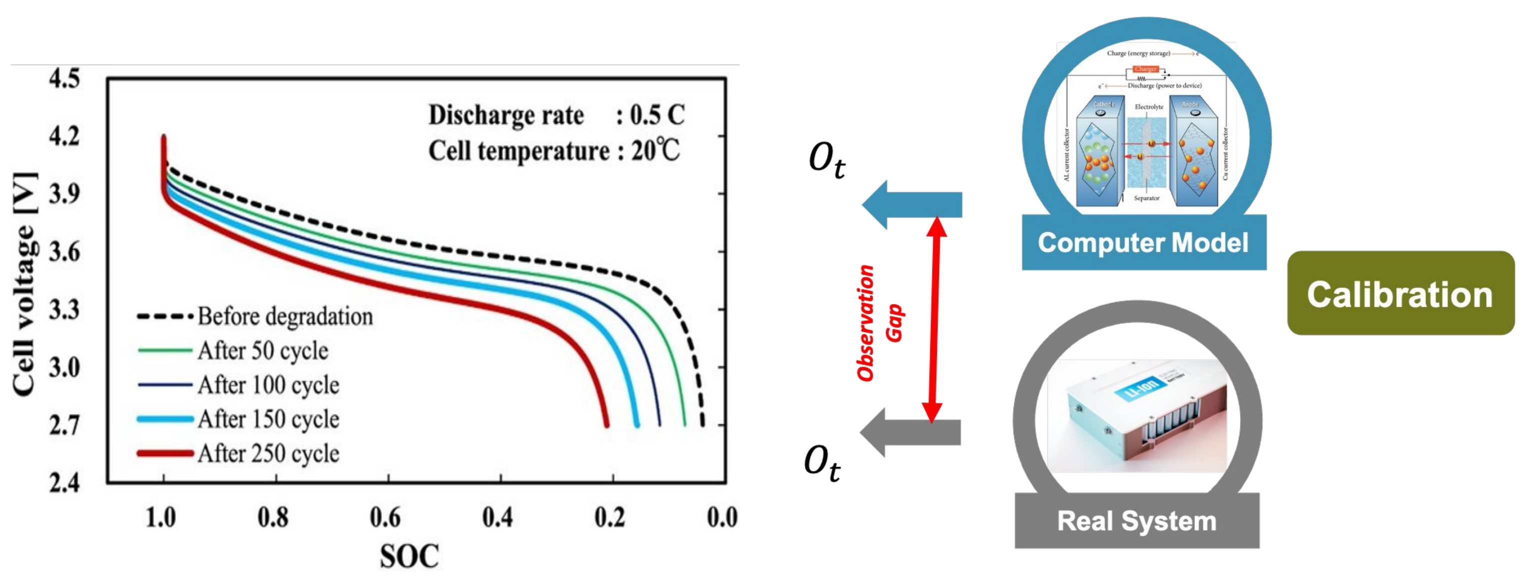
Highlights

- Formulating calibration as a parameter tracking problem
- Reinforcement Learning helps in real-time tracking of battery parameters
- No need of group truth pairs of state and parameters

1. Model calibration is essential in intelligent maintenance of the systems



Detailed electrochemical models enable a good predictions for the EOD of the batteries. However, their parameters are typically calibrated before they are taken into operation and are typically not re-calibrated during operation. Calibration is usually done offline, but this results in the loss of operational capacity. In this work we focus on problem of real-time online calibration of the battery model.

Battery Parameters to Calibrate:

Qmax : Available Lithium Ions in the battery ↓ with time

Ro : Internal resistance of the battery ↑ with time

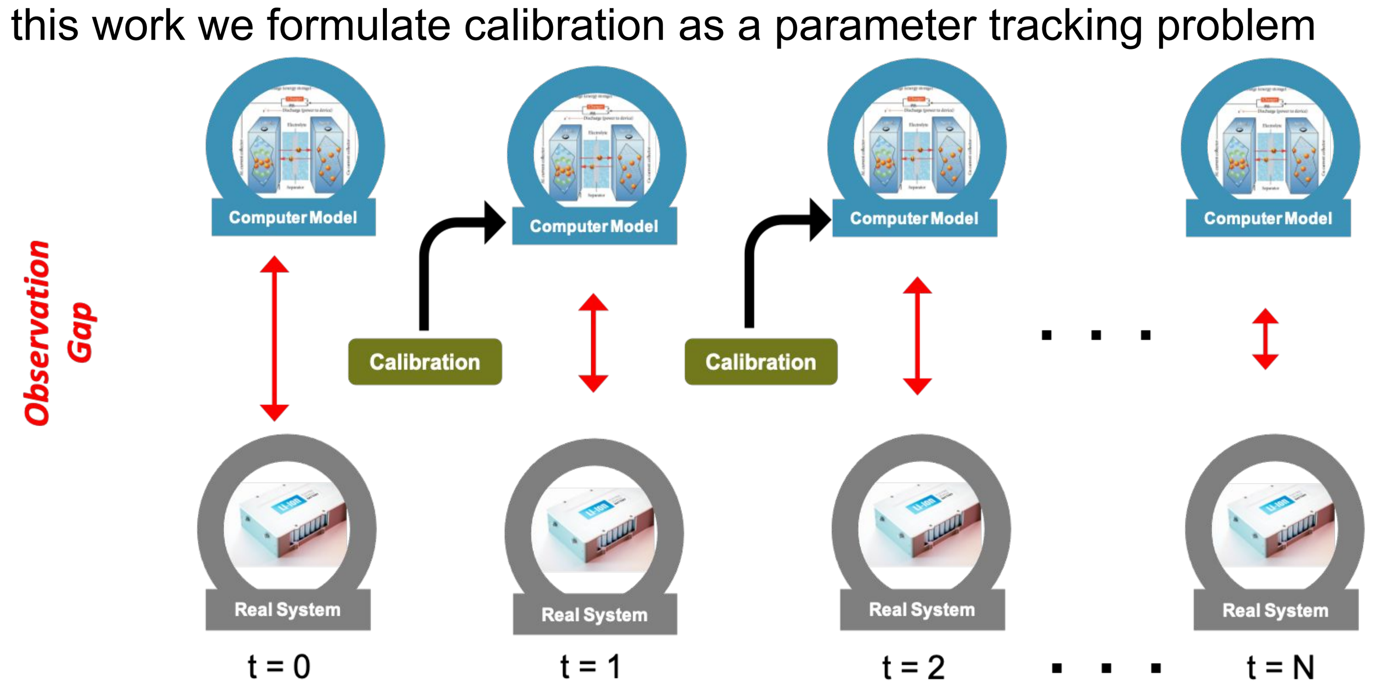
2. Current Calibration Approaches

There are multiple ways the models can be calibrated

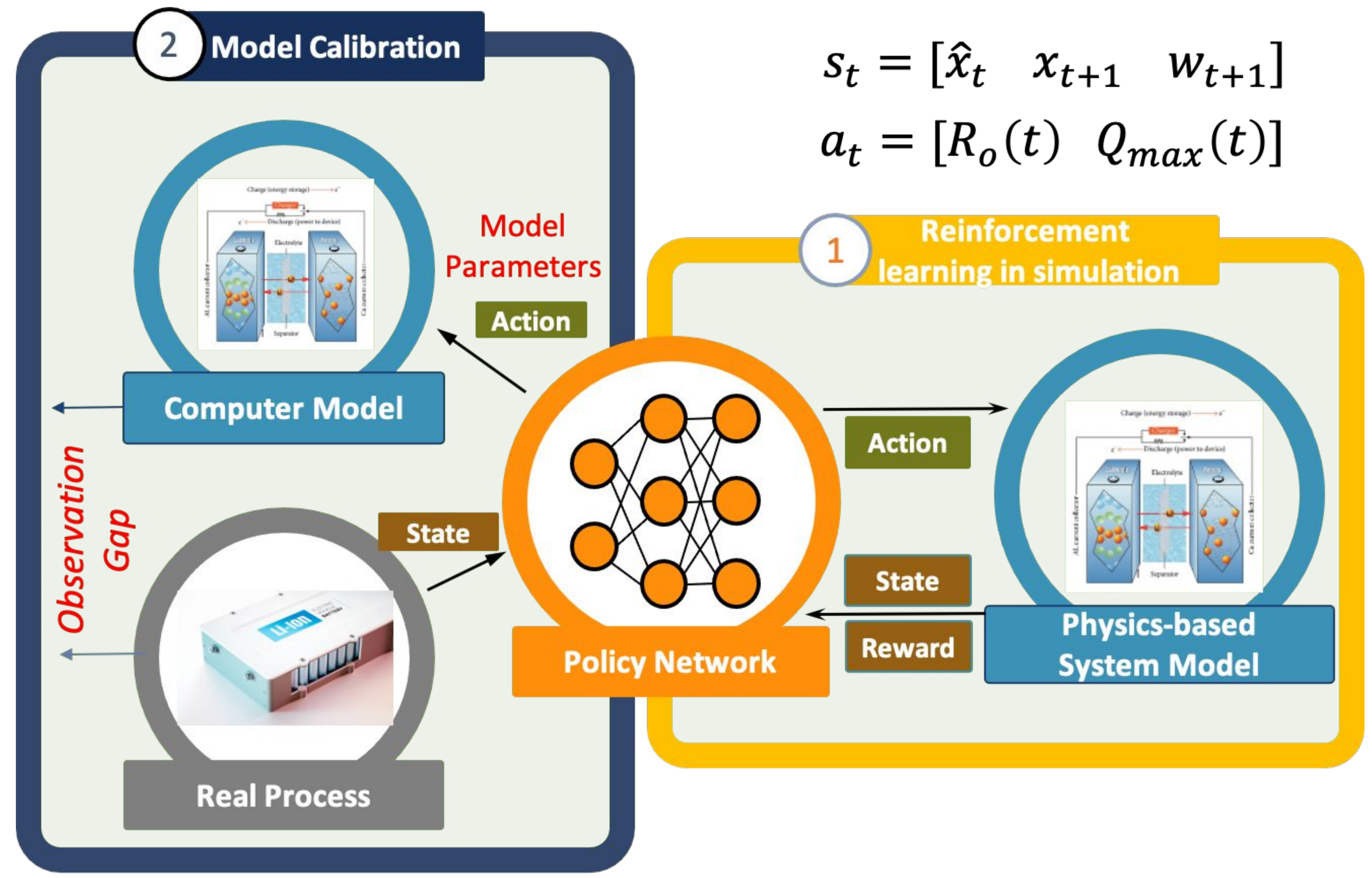
MCMC Very high Computational cost	Particle Filtering High computational cost
System Identification Scalability to large dataset	Supervised learning Representativeness of training data

3. Calibration as tracking

In this work we formulate calibration as a parameter tracking problem



4. Calibration using Reinforcement Learning



$$s_t = [\hat{x}_t \quad x_{t+1} \quad w_{t+1}]$$
$$a_t = [R_o(t) \quad Q_{max}(t)]$$

$\hat{x}_t$ Predicted Battery internal parameters at time **t**

x_{t+1} Actual Battery internal parameters at time **t+1**

w_{t+1} Load condition at time **t+1**

Policy objective has two terms

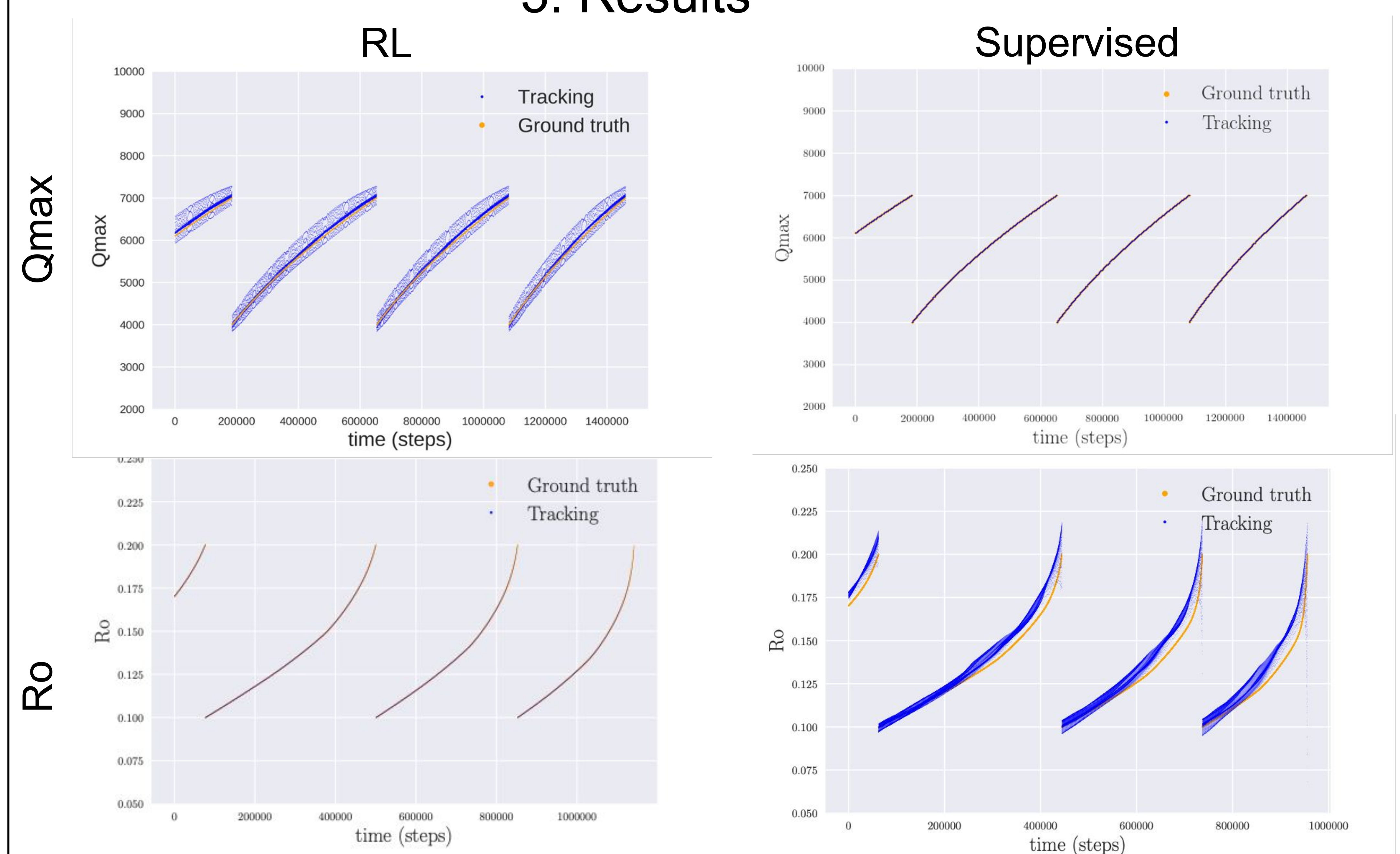
1. Maximum Entropy Reinforcement Learning

$$J(\pi) = \mathbb{E}_{\tau \sim \rho_\pi} \sum_{t=0}^{\infty} [r(s_t, a_t) + \beta \mathcal{H}(\pi(\cdot|s_t))]$$

2. Stability guaranteed lyapunov control

$$\alpha_1 c_\pi(s) \le L(s) \le \alpha_2 c_\pi(s)$$
$$\mathbb{E}_{s\sim\mu_\pi}(\mathbb{E}_{s'\sim P_\pi} L(s') - L(s)) \le -\alpha_3 \mathbb{E}_{s\sim\mu_\pi} c_\pi(s)$$

5. Results



- Accuracy of parameter tracking by RL is comparable to the supervised methods that require groupnd truth state-parameter pairs
- With reinforcement learning we can train a calibrator that is robust against noise in the observations/ environment

6. References

1. Chao, Manuel Arias, et al. "Real-Time Model Calibration with Deep Reinforcement Learning." *arXiv arXiv:2006.04001* (2020)
2. Haarnoja, Tuomas, et al. "Soft actor-critic algorithms and applications." *arXiv arXiv:1812.05905* (2018)
3. Daigle, Matthew J., and Chetan Shrikant Kulkarni. "Electrochemistry-based battery modeling for prognostics." (2013)
4. Han, Minghao, et al. "H∞ Model-free Reinforcement Learning with Robust Stability Guarantee." *CoRR* (2019)

Paper: https://arxiv.org/pdf/2012.04010.pdf

Video: https://bit.ly/2IsUCpo

Code: will be published later

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