# An empirical study of the naïve REINFORCE algorithm for predictive maintenance of industrial milling machines

Rajesh Siraskar

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**Abstract**

In this empirical study, we document the performance of a simple, early reinforcement learning (RL) algorithm, REINFORCE, implemented for a predictive maintenance problem – an optimal tool replacement policy for a milling machine. We compare a naïve implementation of REINFORCE against the policies of industry-grade implementations (Stable-Baselines3) of three advanced algorithms, namely, Deep Q-Network (DQN), Advantage Actor-Critic (A2C) and Proximal Policy Optimization (PPO). This work is aimed at industrial practitioners not accustomed to the complex hyperparameter tuning often required to get RL to work. Our broad goal was to understand the performance of *untuned* algorithms under various scenarios: (1) simulation tool-wear data (2) real tool-wear data (benchmark IEEE NUAA Ideahouse dataset) (3) added noise levels and a random chance of break-down.

Model performance was measured by how accurately the predictive maintenance agent suggested tool replacement when compared to a deterministic preventive maintenance rule based on the tool-wear threshold. Across variants of the environment, REINFORCE models demonstrated a tool replacement precision of 0.687 against 0.449 for A2C, 0.418 for DQN, and 0.472 for PPO. The F1 scores were 0.609, 0.442, 0.374 and 0.345 respectively. Variability in precision and F1 was lower for REINFORCE by 0.08 and 0.016, when compared to the average of the three advanced algorithms. Comparing the *best model* over 10 rounds of training produced surprisingly larger gaps in performance. REINFORCE precision/F1 stood at 0.884/0.873. The best A2C, DQN and PPO models produced 0.520/0.639, 0.651/0.740 and 0.558/0.580 respectively. Our findings indicate that the computationally lightweight REINFORCE performs significantly well for this particular problem. Consequently, for this particular problem, selecting the naïve REINFORCE could be a more suitable and effective policy generating alternative to more advanced complex algorithms.

For reproducibility, model training and testing code, data and the trained REINFORCE models have been uploaded to https://github.com/Link

**Keywords**: Predictive maintenance, milling machines, Reinforcement Learning, REINFORCE

# Abbreviations

| | | | |
|---|---|---|---|
| DQN | Deep Q-Network | A2C | Advantage Actor-Critic |
| PPO | Proximal Policy Optimization | RF | REINFORCE |
| SS | Single-variable state | MS | Multi-variate state |
| TP | True positive | TN | True negative |
| FP | False positive | FN | False negative |
| RL | Reinforcement Learning | SB3 | Stable-Baselines3 |
| PHM | The Prognostics and Health Management Society | *AA* | Advanced Algorithms |

# 1 Introduction

*"Plurality should not be posited without necessity" – Of two competing theories, the simpler explanation of an entity is to be preferred*

— William of Ockham (1285–1347), *The Occams razor principle*

Milling machines are highly versatile, ubiquitous tools serving a variety of industries. A milling machine removes metal from the work piece by rotating and driving a cutting device into it. Abrasive forces cause tool wear, and optimal tool replacement reduces direct costs and optimizes the machines' downtime. With the 2023 milling machine market valued at USD 68.3 billion (Future Market Insights, 2023), this is an important goal for the industry. The cutting tool experiences multiple types of wear as it cuts through metal. Tool wear depends in several factors such as the cutting speed, force applied to the tool, lubrication and materials of the work piece and cutting tool.

Reinforcement learning (RL) is an artificial intelligence technique inspired by nature. Fig. 1 (Sutton and Barto, 2018) shows the RL learning feedback loop. An actor or "agent" interacts with an environment and learns via "trial-and-error". It acts based on stimuli or feedback received from the environment after performing a certain action. Actions that help in achieving the learning goal receive a reward while actions that do not, are punished. Repeating this loop over thousands of episodes, good actions are "reinforced", thereby building a "policy" that is optimized for that goal. In the case of predictive maintenance for milling machines, the agent is the "planner" with a goal of learning an optimal tool replacement policy. The environment consists of sensors attached to the machine and related information such as job specifications, environment conditions etc.

Introduced in 1992, the REINFORCE algorithm (Williams, 1992) is considered as a basic reinforcement learning algorithm. It is a policy-based, on-policy algorithm, capable of handling both discrete and continuous observation and action domains.

In practice the REINFORCE algorithm is considered as a "weak" learner and superseded by several algorithms developed since. Most notably the Q-Learning and its deep-neural network version, the DQN (Mnih et al., 2013),

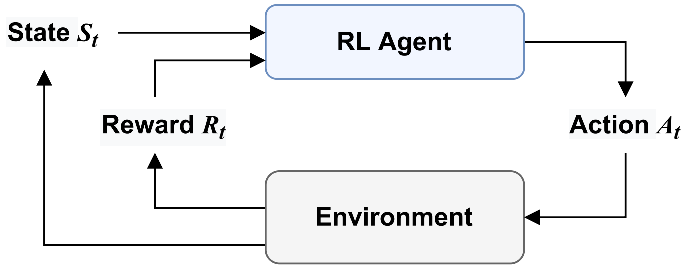


Figure 1: Reinforcement Learning

followed by Actor-Critic (Mnih et al., 2016) and one of the most robust modern-day algorithms, the PPO (Schulman et al., 2017).

## 1.1 Stable-Baselines3

Stable-Baselines3 Raffin et al. (2021), is Open Source and very popular among the RL community[1]. Stable-Baselines3 was initially based on the Open AI baselines (Dhariwal et al., 2017) and is completely rewritten using PyTorch.

for , implementation s the advanced algorithms – DQN, A2C and PPO and compare its performance to a naïve custom implementation of the REINFORCE algorithm. We use Stable-Baselines3 (SB3), the highly popular and reliable implementations of DQN, A2C and PPO. As of 27-Jun-2023, the REINFORCE was not implemented by Stable-Baselines and we therefore custom implemented a basic version.

## 1.2 DQN

Deep Q Network (DQN) builds on Fitted Q-Iteration (FQI) (Riedmiller, 2005) and make use of different tricks to stabilize the learning with neural networks: it uses a replay buffer, a target network and gradient clipping.

## 1.3 REINFORCE

sB-3 dOES NOT IMPLEMENT THE REINFORCE — https://stable-baselines3.readthedocs.io/e

[1]As of 27-Jun-2023, it had 6k+ stars and 424 closed pull requests

Model Free –> Policy Gradient/Actor-Critic –> REINFORCE) REINFORCE (Monte-Carlo policy gradient)

IEEE NUAA Ideahouse dataset has been used in this paper for the RUL estimation of the milling cutter. Yingguang et al. (2021)

Tool wear modeling is the first step to assist in predicting

Literature search conducted on the Scopus™ and Web Of Science™ did not return any articles for the application of reinforcement learning for predictive maintenance of milling machines. Search strings we tried – ‘‘`reinforcement learning AND tool wear AND maintenance", RL + milling + policy, RL + milling + maintenance, RL + tool wear + policy, RL + tool wear + maintenance"`

Running the search ‘‘`reinforcement learning AND milling AND tool wear"` using the Scopus™ and Web Of Science™ services

Dai et al. (2021) is the only article we found that tackles the

Machine learning methods have been applied for example – Oshida et al. (2023) proposes real-time tool wear detection during the milling process. They use a stacked LSTM encoder-decoder model for anomaly detection.

No results for "reinforcement learning" AND "milling machine" AND "tool wear" - on scopus or wos as of 23-jun-2023 "reinforcement learning" AND "milling machine" - 1 not relevant " *Conference Paper* • Open access "Online Learning of Stability Lobe Diagrams in Milling" Friedrich, J. Torzewski, J. Verl, A.

"reinforcement learning" AND "tool wear" - 10 results

# 2 Literature Review

# 3 Method

*The methodology explains in detail what the researcher did to undertake the research. Various aspects of the research have to be outlined: The overall structure and operation of the experiment or observational experience. The groups studied in the research including the size of each group and any fea-*

*tures of the subjects which may be relevant to the topic being researched. The variables that were changed between groups and the variables measured as a result of the changes. The conditions under which the research was undertaken and any factors or variations in conditions which may have an impact on the results. The methods of data analysis used in order to analyse and collate the results. ***Any limitations of the data collected.* We normalize the tool wear and other state features, $x \in [0,\ 1] \subset \mathbb{R}$. This allows for adding white noise of similar magnitudes across experiments of different data-sets

## 3.1 RL environment description

## 3.2 Data description

## 3.3 Procedure

– training
– selecting the model
– conducting the experiments

## 3.4 Evaluation method

## 3.5 Tools

2 different laptops

- why classifction metrics
- why F1beta

## 3.6 Method - training and testing

## 3.7 Precision or Recall?

- Precision => low FP => False replacement-action reduced. *** Unnecessary tool replacement reduced. Tool life maximized, down time minimized,

production disruption minimized
- Recall => low FN => False declaration of normal operation reduced. Reduce missed replacements. Tool replacements increased. *** Product quality not compromised.

## 3.8 Hyper-parameters for Precision or Recall control

- R1 = +1
- R2 = -1
- R3 = -100 => higher neg. Improve recall. Lower neg. Improve precision
- **LOOK AHEAD PARAM**:
- Training: SB3 - 10 k eps. 3 times. Average their outputs
- Testing:
  - Avg. over 5 rounds.
  - Each round - avg over 40 test cases x 10 test rounds
  - Total: 40 x 10 x 5 = 2000 cases
  - Avgs over: 10 rounds (of 40 cases each) X 5 rounds of **re-trained** SB3 agents = 50 rounds

## 3.9 Inference

- Training: SB3 is also unstable - show examples of results such as A2C/DQN 0.00
- Training: SB3 is also unstable - SHOW SB3 tensorboard plots
- Training: SB3 is also unstable - EXCEL plots of results over the 10 rounds

| | A2C | DQN | PPO | REINFORCE |
|---|---|---|---|---|
| Network architecture | input dim x [64\|Tanh x 64\|Tanh] x output dim | input dim x [64\|Tanh x 64\|Tanh] x output dim | input dim x [64\|Tanh x 64\|Tanh] x output dim | input dim x [64\|ReLU] x output dim |
| Layers | 2 | 2 | 2 | 1 |
| Units | 64 x 64 | 64 x 64 | 64 x 64 | 64 |
| Activation | Tanh, Tanh | Tanh, Tanh | Tanh, Tanh | ReLU |
| Optimizer | RMSprop | Adam | Adam | Adam |
| Learning rate | 0.0007 | 0.0001 | 0.0003 | 0.01 |
| Gamma | 0.99 | 0.99 | 0.99 | 0.99 |

Table 1: Comparing the network architecture and basic hyper-parameters across algorithms

# 4 Network architecture and basic hyper-parameters

soure of ppo implementation details https://iclr-blog-track.github.io/2022/03/25/ppo-implementation-details/

source of SB3 network mp : https://github.com/openai/baselines/blob/ea25b9e8b234e6ee1bca43083f8f3cf974143998/baselines/common/models.py#L75-L103

## 4.1 PPO hyperparms

implementation guide source » https://iclr-blog-track.github.io/2022/03/25/ppo-implementation-details/

By default, PPO uses a simple MLP network consisting of two layers of 64 neurons and Hyperbolic Tangent as the activation function. Then PPO builds a policy head and value head that share the outputs of the MLP network. Below is a pseudocode:

### 4.2 dqn hyperparms

default hyperparms : https://stable-baselines3.readthedocs.io/en/master/_modules/stable_baselines3/common/policies.html

overridden in indiv policies for example SB3 DQN hypoerparms for example were taken from ; Paper: https://arxiv.org/abs/1312.5602, https://www.nature.com/articles/ Default hyperparameters are taken from the Nature paper, except for the optimizer and learning rate that were taken from Stable Baselines defaults

# 5 Empirical results

### 5.1 Detailed metrics

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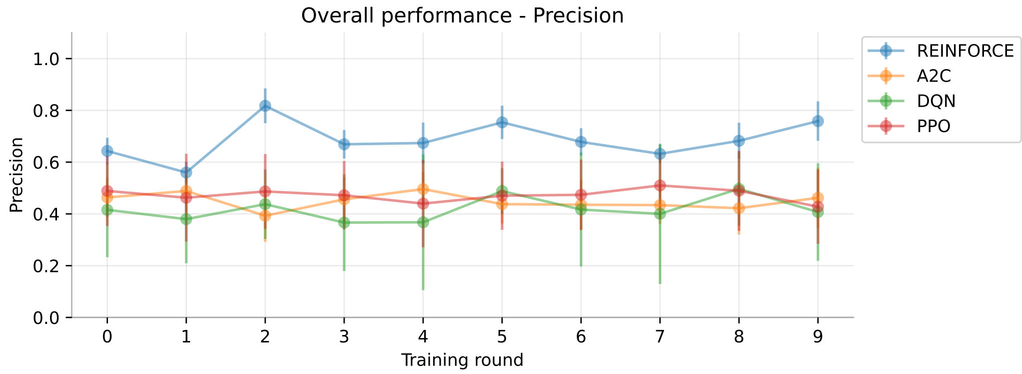
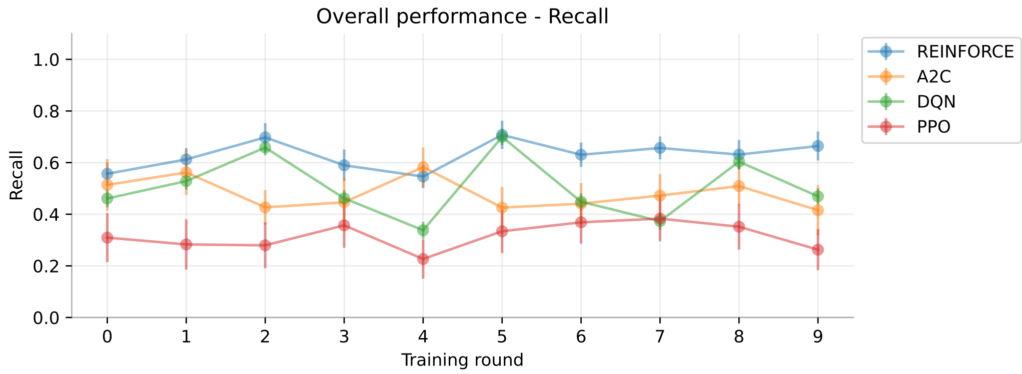
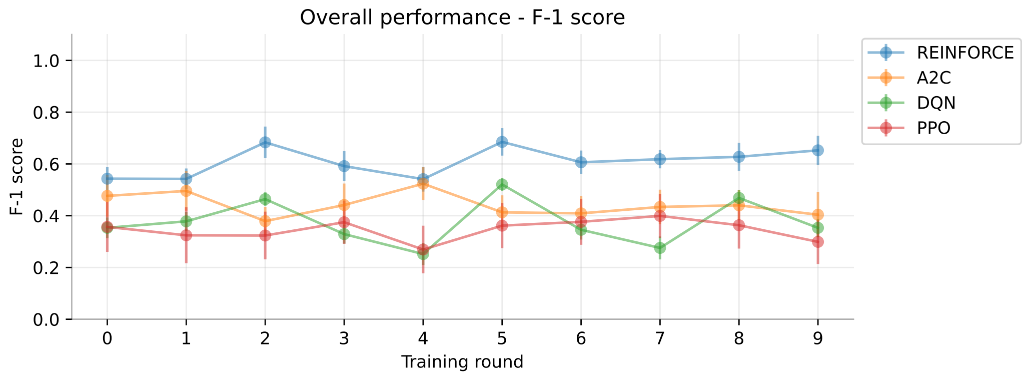


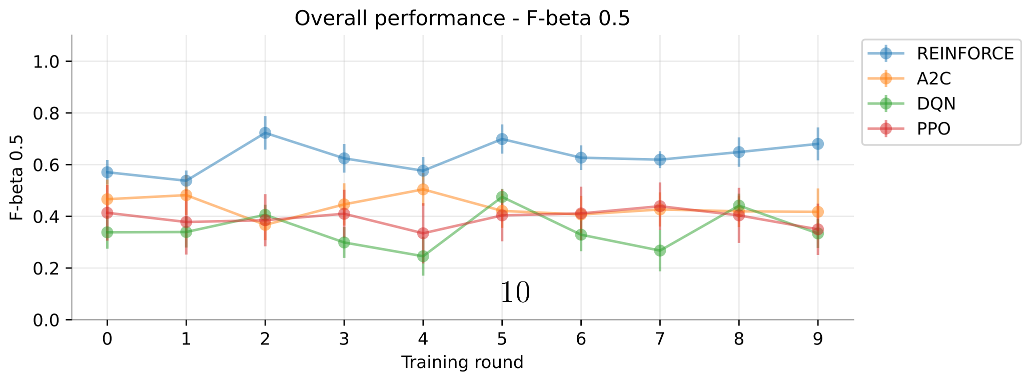

(a) Precision




(b) Recall

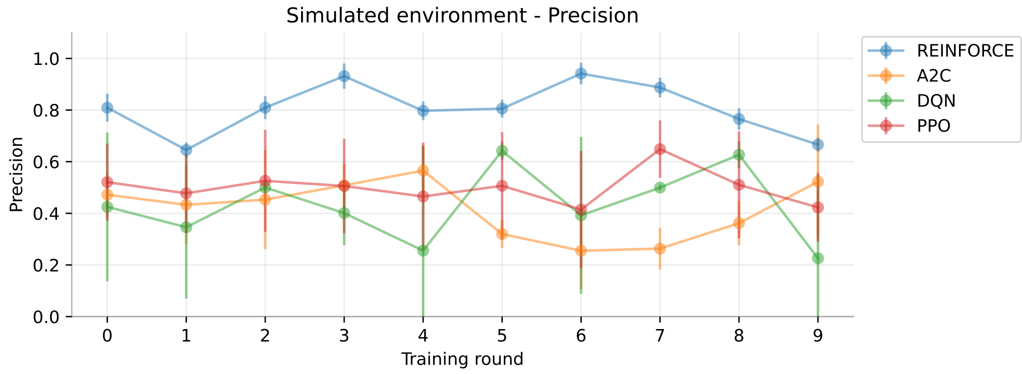



(c) F1-score

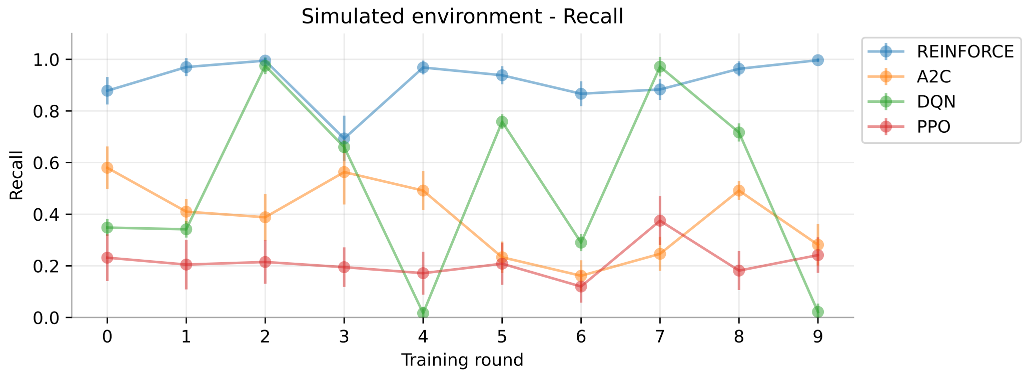



(d) F1-beta (0.5)

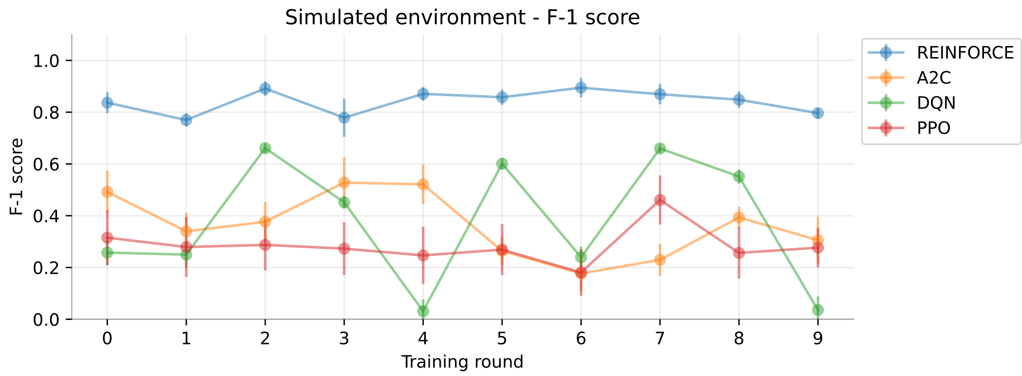
Figure 2: Overall performance – Avg. performance over 10 rounds of model training



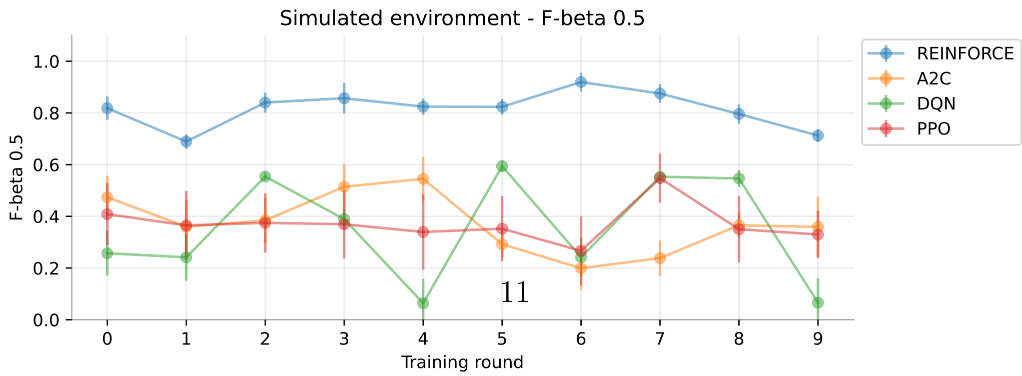

(a) Precision




(b) Recall

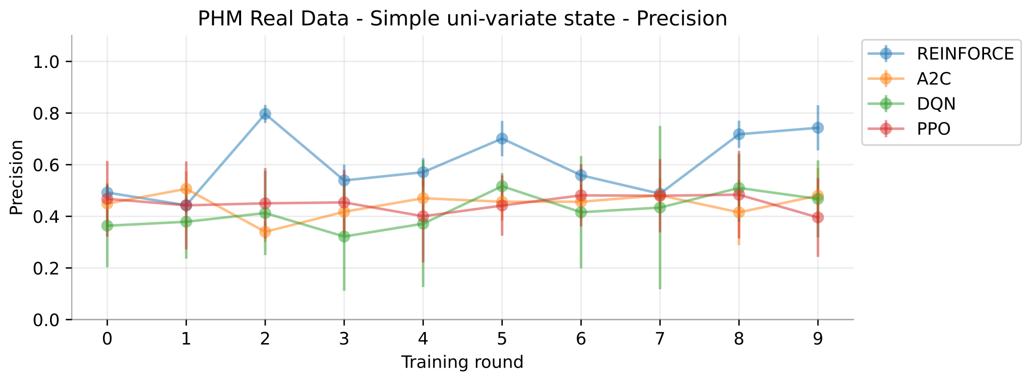



(c) F1-score

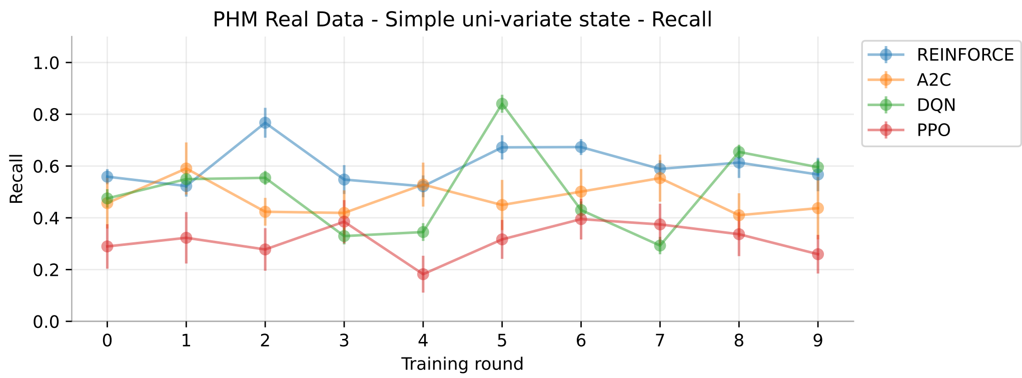



(d) F1-beta (0.5)

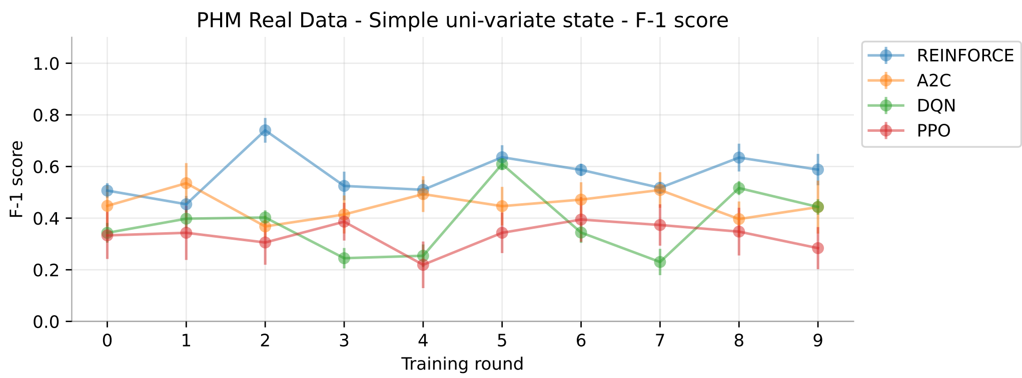
Figure 3: Simulated environment – Avg. performance over 10 rounds of model training



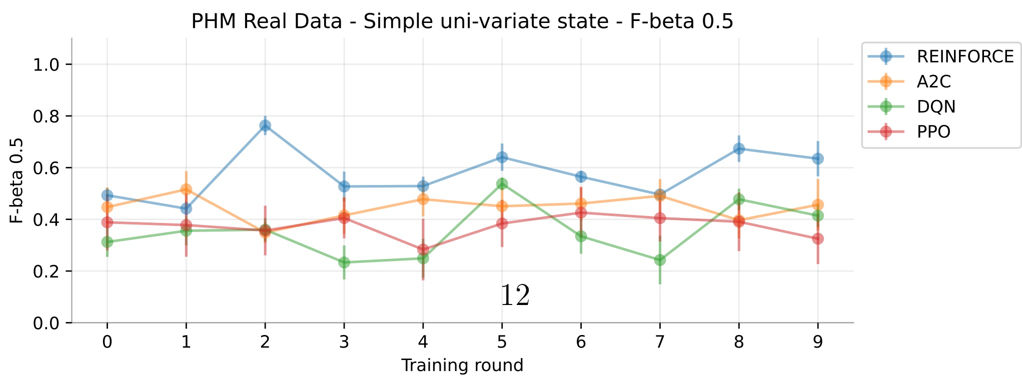

(a) Precision




(b) Recall

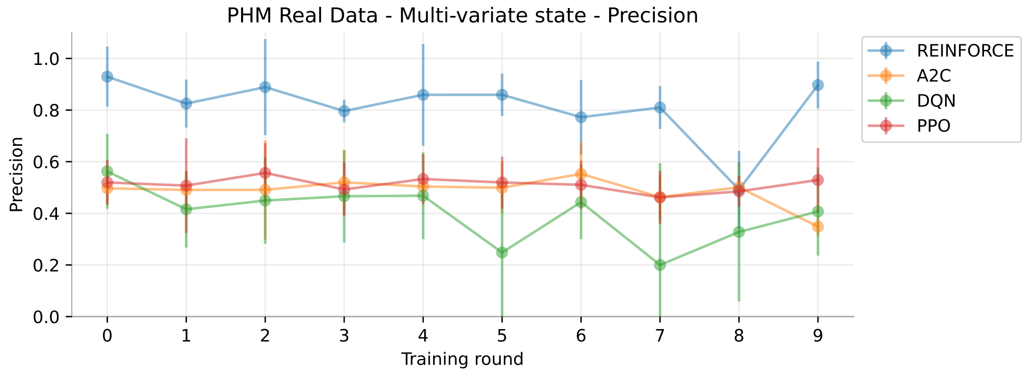



(c) F1-score

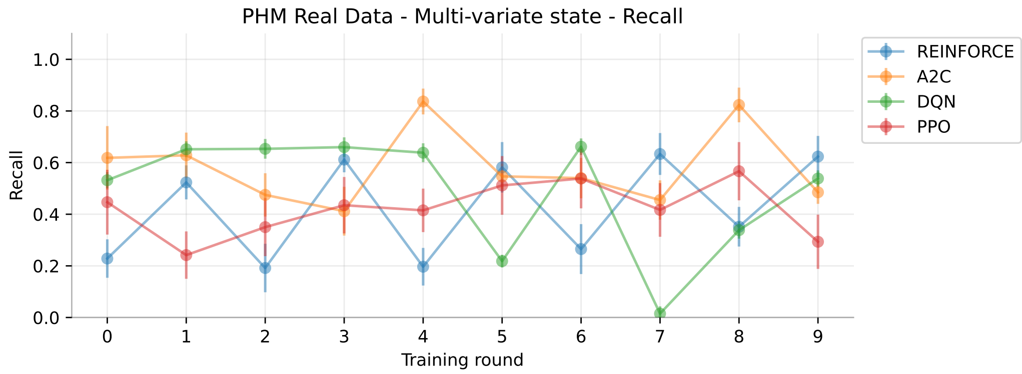



(d) F1-beta (0.5)

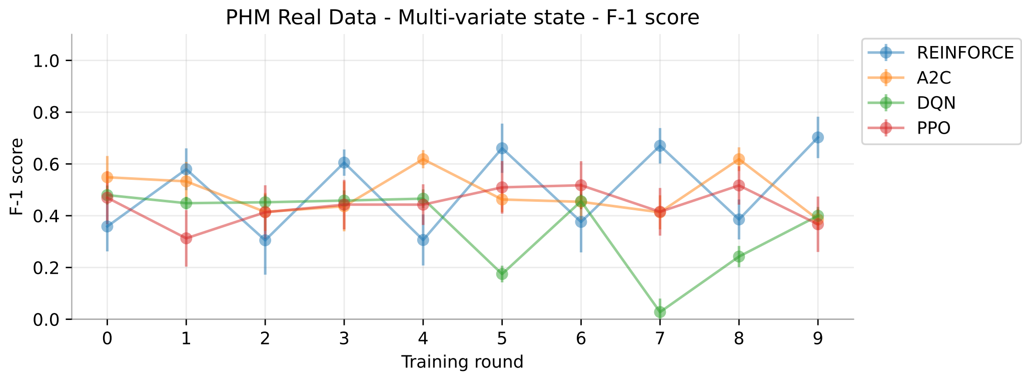
Figure 4: Singe-variable state environment – Avg. performance over 10 rounds of model training



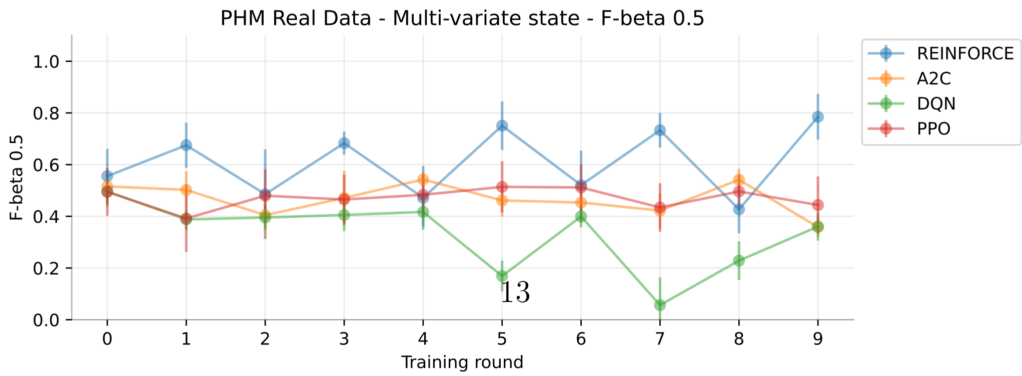

(a) Precision




(b) Recall




(c) F1-score




(d) F1-beta (0.5)

Figure 5: Multi-variate state environment – Avg. performance over 10 rounds of model training

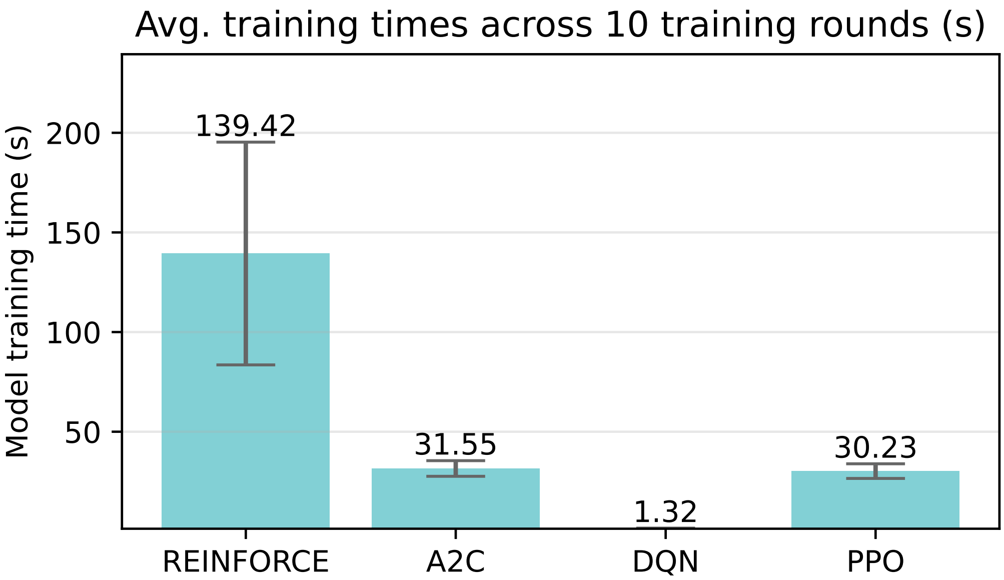



Figure 6: Training time. Across 10 rounds and all environment variants.

| | REINFORCE | | | | A2C | | | | DQN | | | | PPO | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Environment | Prec. | Recall | F1 | F0.5 | Prec. | Recall | F1 | F0.5 | Prec. | Recall | F1 | F0.5 | Prec. | Recall | F1 | F0.5 |
| Simulated - No noise | 0.842 | 0.878 | 0.838 | 0.834 | 0.424 | 0.451 | 0.423 | 0.421 | 0.426 | 0.674 | 0.471 | 0.410 | 0.504 | 0.200 | 0.271 | 0.360 |
| Simulated - Low noise | 0.777 | 0.929 | 0.834 | 0.796 | 0.465 | 0.423 | 0.409 | 0.427 | 0.421 | 0.338 | 0.270 | 0.283 | 0.482 | 0.236 | 0.296 | 0.369 |
| Simulated - High noise | 0.798 | 0.940 | 0.851 | 0.816 | 0.358 | 0.281 | 0.256 | 0.272 | 0.447 | 0.519 | 0.380 | 0.360 | 0.514 | 0.207 | 0.286 | 0.382 |
| PHM C01 SS - No noise | 0.478 | 0.363 | 0.400 | 0.439 | 0.501 | 0.500 | 0.493 | 0.496 | 0.472 | 0.807 | 0.568 | 0.490 | 0.440 | 0.417 | 0.387 | 0.395 |
| PHM C01 SS - Low noise | 0.507 | 0.311 | 0.332 | 0.383 | 0.503 | 0.598 | 0.535 | 0.513 | 0.393 | 0.502 | 0.351 | 0.317 | 0.522 | 0.338 | 0.388 | 0.448 |
| PHM C01 SS - High noise | 0.693 | 0.562 | 0.579 | 0.623 | 0.266 | 0.282 | 0.267 | 0.262 | 0.458 | 0.525 | 0.400 | 0.384 | 0.456 | 0.369 | 0.372 | 0.400 |
| PHM C04 SS - No noise | 0.751 | 0.878 | 0.784 | 0.757 | 0.487 | 0.442 | 0.449 | 0.463 | 0.439 | 0.684 | 0.472 | 0.411 | 0.500 | 0.510 | 0.469 | 0.473 |
| PHM C04 SS - Low noise | 0.662 | 0.756 | 0.672 | 0.657 | 0.409 | 0.455 | 0.428 | 0.416 | 0.411 | 0.500 | 0.370 | 0.341 | 0.488 | 0.280 | 0.324 | 0.386 |
| PHM C04 SS - High noise | 0.611 | 0.713 | 0.620 | 0.598 | 0.518 | 0.607 | 0.552 | 0.530 | 0.358 | 0.451 | 0.325 | 0.294 | 0.428 | 0.262 | 0.286 | 0.333 |
| PHM C06 SS - No noise | 0.830 | 0.726 | 0.754 | 0.792 | 0.517 | 0.509 | 0.507 | 0.511 | 0.360 | 0.309 | 0.256 | 0.258 | 0.409 | 0.248 | 0.275 | 0.321 |
| PHM C06 SS - Low noise | 0.205 | 0.279 | 0.228 | 0.212 | 0.510 | 0.577 | 0.530 | 0.516 | 0.434 | 0.266 | 0.266 | 0.296 | 0.417 | 0.181 | 0.232 | 0.294 |
| PHM C06 SS - High noise | 0.709 | 0.843 | 0.759 | 0.726 | 0.316 | 0.324 | 0.311 | 0.308 | 0.449 | 0.518 | 0.400 | 0.375 | 0.388 | 0.222 | 0.265 | 0.317 |
| PHM C01 MS - No noise | 0.835 | 0.652 | 0.656 | 0.716 | 0.461 | 0.444 | 0.397 | 0.404 | 0.384 | 0.558 | 0.393 | 0.348 | 0.513 | 0.383 | 0.416 | 0.460 |
| PHM C04 MS - No noise | 0.739 | 0.255 | 0.359 | 0.494 | 0.498 | 0.589 | 0.490 | 0.470 | 0.323 | 0.209 | 0.160 | 0.168 | 0.499 | 0.393 | 0.421 | 0.457 |
| PHM C06 MS - No noise | 0.864 | 0.356 | 0.469 | 0.616 | 0.501 | 0.713 | 0.578 | 0.527 | 0.489 | 0.705 | 0.529 | 0.479 | 0.523 | 0.488 | 0.485 | 0.498 |

Table 2: Model performance comparison all variants of the environments, over 10 rounds of training.

### 5.2 Super models metrics

| | REINFORCE | | | | A2C | | | | DQN | | | | PPO | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Environment | Prec. | Recall | F1 | F0.5 | Prec. | Recall | F1 | F0.5 | Prec. | Recall | F1 | F0.5 | Prec. | Recall | F1 | F0.5 |
| Simulated - No noise | 0.897 | 0.960 | 0.926 | 0.908 | 0.500 | 1.000 | 0.667 | 0.556 | 0.505 | 0.980 | 0.667 | 0.560 | 0.669 | 0.430 | 0.518 | 0.597 |
| Simulated - Low noise | 0.960 | 0.945 | 0.952 | 0.957 | 0.516 | 1.000 | 0.680 | 0.571 | 0.500 | 0.980 | 0.662 | 0.554 | 0.633 | 0.460 | 0.530 | 0.586 |
| Simulated - High noise | 0.922 | 0.990 | 0.955 | 0.935 | 0.503 | 1.000 | 0.669 | 0.558 | 0.504 | 0.990 | 0.668 | 0.559 | 0.569 | 0.355 | 0.434 | 0.505 |
| PHM C01 SS - No noise | 0.889 | 0.995 | 0.939 | 0.908 | 0.586 | 0.625 | 0.603 | 0.592 | 0.647 | 0.970 | 0.776 | 0.693 | 0.543 | 1.000 | 0.703 | 0.597 |
| PHM C01 SS - Low noise | 0.988 | 0.765 | 0.861 | 0.932 | 0.499 | 0.995 | 0.664 | 0.554 | 0.504 | 0.990 | 0.668 | 0.559 | 0.623 | 0.740 | 0.675 | 0.643 |
| PHM C01 SS - High noise | 0.850 | 0.970 | 0.905 | 0.871 | 0.521 | 0.680 | 0.588 | 0.546 | 0.505 | 0.985 | 0.668 | 0.560 | 0.520 | 0.725 | 0.604 | 0.551 |
| PHM C04 SS - No noise | 0.811 | 1.000 | 0.895 | 0.842 | 0.536 | 0.645 | 0.583 | 0.554 | 0.501 | 0.965 | 0.660 | 0.554 | 0.579 | 0.895 | 0.702 | 0.622 |
| PHM C04 SS - Low noise | 0.798 | 0.980 | 0.879 | 0.829 | 0.556 | 0.665 | 0.603 | 0.573 | 0.734 | 0.990 | 0.843 | 0.774 | 0.546 | 0.660 | 0.596 | 0.565 |
| PHM C04 SS - High noise | 0.708 | 0.840 | 0.767 | 0.730 | 0.521 | 0.835 | 0.641 | 0.563 | 0.511 | 0.985 | 0.672 | 0.565 | 0.517 | 0.820 | 0.633 | 0.558 |
| PHM C06 SS - No noise | 1.000 | 0.895 | 0.944 | 0.977 | 0.520 | 0.680 | 0.587 | 0.545 | 0.935 | 0.975 | 0.954 | 0.942 | 0.587 | 0.650 | 0.615 | 0.597 |
| PHM C06 SS - Low noise | 0.943 | 0.795 | 0.861 | 0.908 | 0.501 | 1.000 | 0.668 | 0.557 | 0.961 | 0.725 | 0.826 | 0.901 | 0.552 | 0.370 | 0.438 | 0.497 |
| PHM C06 SS - High noise | 0.821 | 0.845 | 0.831 | 0.825 | 0.540 | 0.755 | 0.628 | 0.572 | 0.980 | 0.960 | 0.969 | 0.976 | 0.521 | 0.615 | 0.564 | 0.537 |
| PHM C01 MS - No noise | 0.827 | 0.995 | 0.903 | 0.856 | 0.500 | 1.000 | 0.667 | 0.556 | 0.505 | 0.985 | 0.668 | 0.560 | 0.512 | 0.595 | 0.549 | 0.526 |
| PHM C04 MS - No noise | 0.910 | 0.425 | 0.577 | 0.738 | 0.500 | 1.000 | 0.667 | 0.556 | 0.501 | 0.975 | 0.662 | 0.555 | 0.501 | 0.635 | 0.558 | 0.522 |
| PHM C06 MS - No noise | 0.934 | 0.865 | 0.896 | 0.918 | 0.500 | 1.000 | 0.667 | 0.556 | 0.969 | 0.600 | 0.741 | 0.863 | 0.497 | 0.690 | 0.577 | 0.526 |

Table 3: Super Models: Best models selected over 10 rounds of training.

## 5.3 Overall summary performance

| | Precision | | Recall | | F1-score | | F1-beta score | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| A2C | 0.449 | 0.088 | 0.480 | 0.084 | 0.442 | 0.070 | 0.436 | 0.071 |
| DQN | 0.418 | 0.185 | 0.504 | 0.032 | 0.374 | 0.035 | 0.348 | 0.058 |
| PPO | 0.472 | 0.144 | 0.316 | 0.087 | 0.345 | 0.091 | 0.393 | 0.105 |
| REINFORCE | 0.687 | 0.059 | 0.629 | 0.051 | 0.609 | 0.050 | 0.631 | 0.052 |

Table 4: Model performance summary - averaged over all environment.

## 5.4 Simulated environment

| | Precision | | Recall | | F1-score | | F1-beta score | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| A2C | 0.416 | 0.120 | 0.385 | 0.073 | 0.363 | 0.072 | 0.373 | 0.082 |
| DQN | 0.432 | 0.184 | 0.510 | 0.031 | 0.374 | 0.034 | 0.351 | 0.056 |
| PPO | 0.500 | 0.178 | 0.215 | 0.081 | 0.285 | 0.099 | 0.370 | 0.122 |
| REINFORCE | 0.806 | 0.040 | 0.915 | 0.038 | 0.841 | 0.035 | 0.816 | 0.037 |

Table 5: Model performance summary - averaged over simulated environments.

### 5.5 Real data – simple uni-variate environment

| | Precision | | Recall | | F1-score | | F1-beta score | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| A2C | 0.447 | 0.077 | 0.477 | 0.091 | 0.452 | 0.072 | 0.446 | 0.070 |
| DQN | 0.419 | 0.179 | 0.507 | 0.032 | 0.379 | 0.036 | 0.352 | 0.057 |
| PPO | 0.450 | 0.146 | 0.314 | 0.082 | 0.333 | 0.087 | 0.374 | 0.102 |
| REINFORCE | 0.605 | 0.046 | 0.603 | 0.046 | 0.570 | 0.041 | 0.576 | 0.040 |

Table 6: Model performance summary - averaged over PHM-2010 environments with simple single-variable environment.

### 5.6 Real data – complex multi-variate state

| | Precision | | Recall | | F1-score | | F1-beta score | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| A2C | 0.487 | 0.086 | 0.582 | 0.075 | 0.488 | 0.063 | 0.467 | 0.065 |
| DQN | 0.399 | 0.204 | 0.491 | 0.032 | 0.361 | 0.035 | 0.332 | 0.060 |
| PPO | 0.512 | 0.107 | 0.422 | 0.107 | 0.441 | 0.096 | 0.472 | 0.096 |
| REINFORCE | 0.813 | 0.119 | 0.421 | 0.079 | 0.495 | 0.090 | 0.609 | 0.101 |

Table 7: Model performance summary - averaged over PHM-2010 environments with complex multi-variate environment.

### 5.7 Hypothesis testing

$$\left.\begin{aligned} H_0 &: \mu_{RF} - \mu_{AA} = 0, \\ H_a &: \mu_{RF} - \mu_{AA} > 0, \end{aligned}\right\} \qquad \forall \;\; AA \in [A2C, DQN, PPO] \tag{1}$$

| Metric | p Value | | | t Statistic | | |
|---|---|---|---|---|---|---|
| | RF $\underset{H_0}{\overset{H_a}{\geqq}}$ A2C | RF $\underset{H_0}{\overset{H_a}{\geqq}}$ DQN | RF $\underset{H_0}{\overset{H_a}{\geqq}}$ PPO | RF $\underset{H_0}{\overset{H_a}{\geqq}}$ A2C | RF $\underset{H_0}{\overset{H_a}{\geqq}}$ DQN | RF $\underset{H_0}{\overset{H_a}{\geqq}}$ PPO |
| **Overall** (1500 samples) | | | | | | |
| Precision | 4.31E-126 | 2.17E-109 | 2.81E-106 | 25.071 | 23.170 | 22.804 |
| Recall | 4.20E-35 | 3.37E-16 | 4.36E-150 | 12.522 | 8.206 | 27.650 |
| F1 score | 1.99E-64 | 1.46E-88 | 5.29E-155 | 17.364 | 20.634 | 28.160 |
| **Simulated environment** (300 samples) | | | | | | |
| Precision | 3.20E-98 | 1.69E-63 | 2.65E-81 | 25.611 | 19.032 | 22.427 |
| Recall | 8.12E-104 | 2.56E-41 | 1.57E-264 | 26.665 | 14.558 | 62.541 |
| F1 score | 9.60E-134 | 8.56E-99 | 2.96E-242 | 32.402 | 25.719 | 56.575 |
| **PHM Real data - Simple uni-variate state** (900 samples) | | | | | | |
| Precision | 2.27E-32 | 7.29E-31 | 9.95E-31 | 12.082 | 11.770 | 11.742 |
| Recall | 1.27E-16 | 1.55E-06 | 8.19E-71 | 8.357 | 4.821 | 18.607 |
| F1 score | 1.94E-19 | 4.67E-34 | 2.19E-67 | 9.121 | 12.423 | 18.098 |
| **PHM Real data - Complex multi-variate state** (300 samples) | | | | | | |
| Precision | 1.64E-60 | 3.34E-54 | 7.88E-59 | 18.451 | 17.207 | 18.122 |
| Recall | 2.69E-10 | 2.69E-02 | 9.68E-01 | -6.425 | -2.219 | -0.041 |
| F1 score | 7.27E-01 | 1.44E-08 | 1.35E-03 | 0.349 | 5.748 | 3.220 |

Table 8: One-tail t-test - Ho: No difference in metrics. Ha: REINFORCE metric > Advanced algorithm metric

## 5.8 Training times

# 6 Environment description

## 6.1 simulated data

(Dašić, 2006). eq 16 from the paper parameters b0, b1, b2 and a under the form of a complex power-exponential regression equation power functions as approximating functions of cutting tool wear, we proposed is powerexponential function form

tool flank wear VB

$$VB = a \cdot t^{b_1} \cdot e^{b_2 \cdot t}\Big|_{t=t_0}^{t=t_1}$$

b0 -2.4941 b1 0.3342 b2 0.03147 a 0.08257 Determination of Complex Power- Exponential Regression Equation for Functional Dependence between Tool Wear and Cutting Time for Cutting Speed v=79.2 [m/min] Parameter calculation b0, b1 and b2 of the linear regression for the mentioned example is consisted in the solving of the normal system equation (12) with the following shape:

**Implementation details**: Normalization

init

reset

reward function

degradation model as exponential

$$H(t) = 1 - D_0 - \mathrm{e}^{(at^b)}, \tag{2}$$

where, $D_0$ is the initial degradation state while $a$ and $b$ are wear-rate coefficients that depend on the effect of temperature, vibration and other system stress parameters

$$X(m,n) = \left\{ \begin{array}{ll} x(n), & \text{for } 0 \leq n \leq 1 \\ x(n-1), & \text{for } 0 \leq n \leq 1 \\ x(n-1), & \text{for } 0 \leq n \leq 1 \end{array} \right\} = xy$$

$$R_t = \begin{cases} 0, & \text{if } U(s_t) = U(s_{t+1}) = 0 \\ -1.0, & \text{if } U(s_t) = 0, U(s_{t+1}) = 1 \\ R_{ff}, & \text{if } U(s_t) = 1 \end{cases} \tag{3}$$

## 6.2 SS

```
def _get_observation(self, index):
next_state = np.array([
self.df['time'][index],
self.df['tool_wear'][index]
], dtype=np.float32)

return next_state
```

## 6.3 MS

```
def _get_observation(self, index):
next_state = np.array([
self.df['tool_wear'][index],
self.df['force_x'][index],
self.df['force_y'][index],
self.df['force_z'][index],
self.df['vibration_x'][index],
self.df['vibration_y'][index],
self.df['vibration_z'][index],
self.df['acoustic_emission_rms'][index]
], dtype=np.float32)

return next_state

# Machine data frame properties
self.df = df
self.df_length = len(self.df.index)
```

```
self.df_index = 0

# Milling operation and tool parameters
self.wear_threshold = wear_threshold
self.max_operations = max_operations
self.breakdown_chance = breakdown_chance
self.add_noise = add_noise
self.R1 = R1
self.R2 = R2
self.R3 = R3
self.reward = 0.0
```

### 6.4 main env

```
env = MillingTool_SS_NT(df_train, WEAR_THRESHOLD_NORMALIZED, MILLING_OPERATIONS_
```

### 6.5 test env

```
env_test = MillingTool_SS_NT(df_test, WEAR_THRESHOLD_ORG_NORMALIZED, MILLING_OPE
```

## 7 The core elements of the 4 algorithms

The core elements of the 4 algorithms. (Graesser and Keng, 2019)

**REINFORCE**: Paper (Williams, 1992)

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_t \left[\, R_t(\tau)\ \nabla_\theta \ln \pi_\theta(a_t|s_t)\, \right] \tag{4}$$

**DQN**: Learning Q-function in DQN. Paper (Mnih et al., 2013). Implementation notes: "*SB3 says:* Deep Q Network (DQN) builds on Fitted Q-Iteration (FQI) and make use of different tricks to stabilize the learning with neural networks: it uses a replay buffer, a target network and gradient clipping"

$$Q^\pi(s,a) = r + \gamma \max_{a'} Q^\pi(s',a') \tag{5}$$

**A2C**: Actors learn parameterized policy $\pi_\theta$ using the policy-gradient as shown in Equation 6. "*SB3 says:* A synchronous, deterministic variant of Asynchronous Advantage Actor Critic (A3C). It uses multiple workers to avoid the use of a replay buffer.". Paper (Mnih et al., 2016)

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_t \left[ \; A_t^\pi \; \nabla_\theta \ln \pi_\theta(a_t|s_t) \; \right] \tag{6}$$

Where the advantage function $A_t^\pi(s_t, a_t)$ measures how good or bad the action is w.r.t. policy's average, for a particular state using Equation 7

$$A_t^\pi(s_t, a_t) = Q^\pi(s_t, a_t) - V^\pi(s_t) \tag{7}$$

**PPO**: " *SB3 says:* The Proximal Policy Optimization algorithm combines ideas from A2C (having multiple workers) and TRPO (it uses a trust region to improve the actor). The main idea is that after an update, the new policy should be not too far from the old policy. For that, ppo uses clipping to avoid too large update.". Paper (Schulman et al., 2017)

$$J^{CLIP}(\theta) = \mathbb{E}_t \left[ \; min(r_t(\theta) A_t^{\pi_{\theta_{old}}}, clip(r_t(\theta), 1-\epsilon, 1+\epsilon) A_t^{\pi_{\theta_{old}}}) \right] \tag{8}$$

# 8 The REINFORCE algorithm

Three key features of any RL algorithm:

1. Policy: $\pi_\theta$ = Probablities of all actions, given a state. Parameterized by $\theta$

2. Objective function:

$$\max_\theta J(\pi_\theta) = \mathop{\mathbb{E}}_{\tau \sim \pi_\theta} [R(\tau)] \tag{9}$$

3. Method: Way to udate the parameters = Policy Gradient

## 8.1 Policy gradient numerical computation

1. Plain vanilla:

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_{\tau \sim \pi_\theta} \left[ \sum_{t=0}^{T} R_t(\tau) \nabla_\theta \ln \pi_\theta(a_t|s_t) \right] \tag{10}$$

2. With Monte Carlo sampling and approximation: $\nabla_\theta J(\pi_\theta) \approx [\, \sum_{t=0}^{T} R_t(\tau) \nabla_\theta \ln \pi_\theta(a_t|s_t) \,]$

3. With baseline: $\nabla_\theta J(\theta) \approx [\, \sum_{t=0}^{T} (R_t(\tau) - b(s_t)) \nabla_\theta \ln \pi_\theta(a_t|s_t) \,]$

4. Where, baseline does not change per time-step, it is for the entire trajectory

5. One baseline option: $V^\pi$ - leads to Actor-Critic algorithm

6. Simpler option: Average returns over trajectory: $b = \frac{1}{T} \sum_{t=0}^{T} R_t(\tau)$

Algorithm

# 9 Discussion

## 9.1 Precision or Recall?

- Precision => low FP => False replacement-action reduced. *** Unnecessary tool replacement reduced. Tool life maximized, down time minimized, production disruption minimized
- Recall => low FN => False declaration of normal operation reduced. Reduce missed replacements. Tool replacements increased. *** Product quality not compromised.

limitiongs of the slecting model for evaluation

Raffin et al. (2021) – quote from paper - intro section – "A major challenge is that small implementation details can have a substantial effect on performance often greater than the difference between algorithms (Engstrom et al., 2020). It is particularly important that implementations used as experimental baselines are reliable; otherwise, novel algorithms compared to weak baselines lead to inated estimates of performance improvements"

DPO paper - Rafael Rafailov May-2023 — Direct Preference Optimization: Your Language Model is Secretly a Reward Model

5.2 Instability of Actor-Critic Algorithms We can also use our framework to diagnose instabilities with standard actor-critic algorithms used for the RLHF, such as PPO. We follow the RLHF pipeline and focus on the RL fine-tuning step outlined in Section 3. We can draw connections to the control as inference framework [18] for the constrained RL problem outlined in 3. We assume a parameterized model and minimize This is the same objective optimized in prior works [45, 35, 1, 23] using the DPO-equivalent reward for the reward class of In this setting, we can interpret the normalization term in as the soft value function of the reference policy . While this term does not affect the optimal solution, without it, the policy gradient of the objective could have high variance, making learning unstable. We can accommodate for the normalization term using a learned value function, but that can also be difficult to optimize. Alternatively, prior works have normalized rewards using a human completion baseline, essentially a single sample Monte-Carlo estimate of the normalizing term. In contrast the DPO reparameterization yields a reward function that does not require any baselines.

# 10 Conclusion

# References

Zixiang Dai, Mingyan Jiang, Xiaogang Li, Dongfeng Yuan, and Xiaotian Zhou. Reinforcement lion swarm optimization algorithm for tool wear prediction. In *2021 Global Reliability and Prognostics and Health Management (PHM-Nanjing)*, pages 1–7. IEEE, 2021.

Predrag Dašić. Analysis of wear cutting tools by complex power-exponential function for finishing turning of the hardened steel 20crmo5 by mixed ceramic tools. *Fascicle VIII Tribology*, 12:54–60, 2006.

Prafulla Dhariwal, Christopher Hesse, Oleg Klimov, Alex Nichol, Matthias Plappert, Alec Radford, John Schulman, Szymon Sidor, Yuhuai Wu, and Peter Zhokhov. Openai baselines. https://github.com/openai/baselines, 2017.

Future Market Insights. Milling machine market outlook (2023 to 2033), 1 2023. URL https://www.futuremarketinsights.com/reports/milling-machine-market. Accessed: 2023-06-23.

Laura Graesser and Wah Loon Keng. *Foundations of deep reinforcement learning*. Addison-Wesley Professional, 2019.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International conference on machine learning*, pages 1928–1937. PMLR, 2016.

Taisuke Oshida, Tomohiro Murakoshi, Libo Zhou, Hirotaka Ojima, Kazuki Kaneko, Teppei Onuki, and Jun Shimizu. Development and implementation of real-time anomaly detection on tool wear based on stacked lstm encoder-decoder model. *The International Journal of Advanced Manufacturing Technology*, pages 1–16, 2023.

Antonin Raffin, Ashley Hill, Adam Gleave, Anssi Kanervisto, Maximilian Ernestus, and Noah Dormann. Stable-baselines3: Reliable reinforcement learning implementations. *J. Mach. Learn. Res.*, 22(1), jan 2021. ISSN 1532-4435.

Martin Riedmiller. Neural fitted q iteration–first experiences with a data efficient neural reinforcement learning method. In *Machine Learning: ECML 2005: 16th European Conference on Machine Learning, Porto, Portugal, October 3-7, 2005. Proceedings 16*, pages 317–328. Springer, 2005.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Richard Sutton and Andrew Barto. *Reinforcement Learning: An Introduction*. The MIT Press, Cambridge, England, 2nd. edition edition, 2018.

Ronald J Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Reinforcement learning*, pages 5–32, 1992.

LI Yingguang, LIU Changqing, LI Dehua, HUA Jiaqi, and WAN Peng. Tool wear dataset of nuaa ideahouse, 2021. URL https://dx.doi.org/10.21227/3aa1-5e83.