# Experiments with REINFORCE algorithm

Rajesh Siraskar

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# Agenda

1. Objective
2. The RL environment
3. Evaluation strategy
4. Findings
5. Discussion

# Objectives

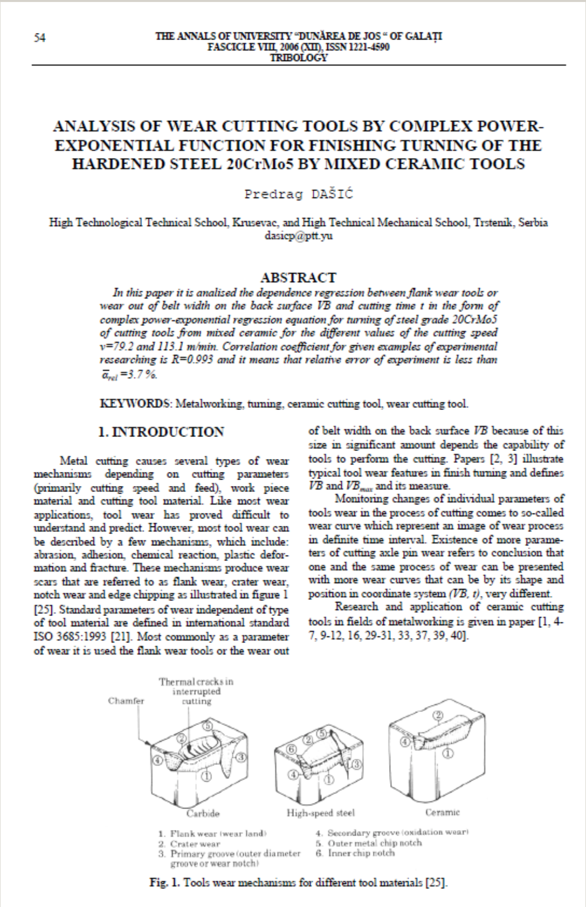
Research goal*: An optimal predictive maintenance policy for replacement of milling tool

1. Experiment with the very *basic, naïve*, REINFORCE algorithm
2. Implemented from "scratch" (Bigger objective: Start with basic REINFORCE, then keep improving it)
3. Compare against industry grade implementation of DQN, A2C and PPO (Stable-Baselines-3)
4. This is a purely experimental (empirical) exercise.

# RL environment

Two different sources – simulated and real milling data

$$VB = a \cdot t^{b_1} \cdot e^{b_2 \cdot t} \Bigg|_{t=0}^{t=t_k}$$



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TRIBOLOGY

ANALYSIS OF WEAR CUTTING TOOLS BY COMPLEX POWER-EXPONENTIAL FUNCTION FOR FINISHING TURNING OF THE HARDENED STEEL 20CrMo5 BY MIXED CERAMIC TOOLS

Predrag DAŠIĆ

High Technological Technical School, Krusevac, and High Technical Mechanical School, Trstenik, Serbia
dasicp@ptt.yu

ABSTRACT

*In this paper it is analised the dependence regression between flank wear tools or wear out of belt width on the back surface VB and cutting time t in the form of complex power-exponential regression equation for turning of steel grade 20CrMo5 of cutting tools from mixed ceramic for the different values of the cutting speed v=79.2 and 113.1 m/min. Correlation coefficient for given examples of experimental researching is R=0.993 and it means that relative error of experiment is less than* $\bar{\alpha}_{rel} = 3.7$ %.

KEYWORDS: Metalworking, turning, ceramic cutting tool, wear cutting tool.

1. INTRODUCTION

Metal cutting causes several types of wear mechanisms depending on cutting parameters (primarily cutting speed and feed), work piece material and cutting tool material. Like most wear applications, tool wear has proved difficult to understand and predict. However, most tool wear can be described by a few mechanisms, which include: abrasion, adhesion, chemical reaction, plastic deformation and fracture. These mechanisms produce wear scars that are referred to as flank wear, crater wear, notch wear and edge chipping as illustrated in figure 1 [25]. Standard parameters of wear independent of type of tool material are defined in international standard ISO 3685:1993 [21]. Most commonly as a parameter of wear it is used the flank wear tools or the wear out of belt width on the back surface *VB* because of this size in significant amount depends the capability of tools to perform the cutting. Papers [2, 3] illustrate typical tool wear features in finish turning and defines *VB* and $VB_{max}$ and its measure.

Monitoring changes of individual parameters of tools wear in the process of cutting comes to so-called wear curve which represent an image of wear process in definite time interval. Existence of more parameters of cutting axle pin wear refers to conclusion that one and the same process of wear can be presented with more wear curves that can be by its shape and position in coordinate system *(VB, t)*, very different.

Research and application of ceramic cutting tools in fields of metalworking is given in paper [1, 4-7, 9-12, 16, 29-31, 33, 37, 39, 40].



Fig. 1. Tools wear mechanisms for different tool materials [25].

◄ Simulated. Dašić, Predrag (2006): Analysis of wear cutting tools by complex power exponential function for finishing turning of the hardened steel 20CrMo5 by mixed ceramic tools.

▼ Real data. IEEE – PHM Society

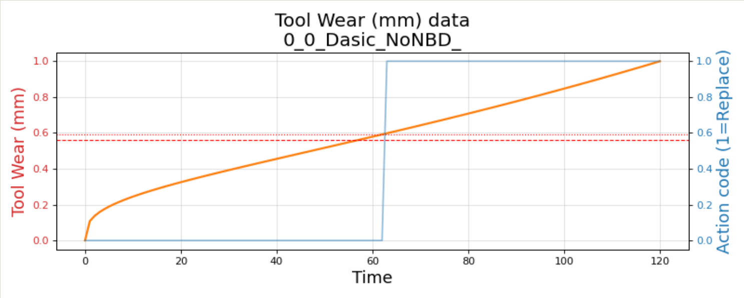
# RL environment - Variants

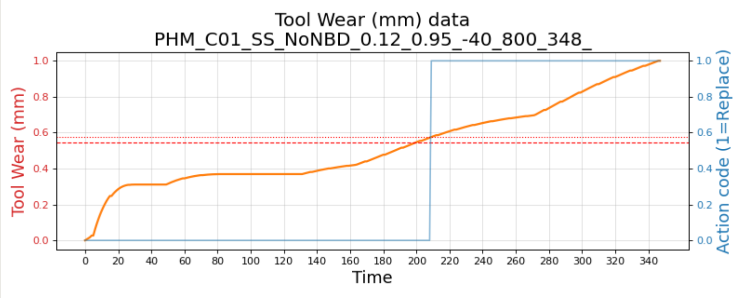
**Three environments and their variants:**

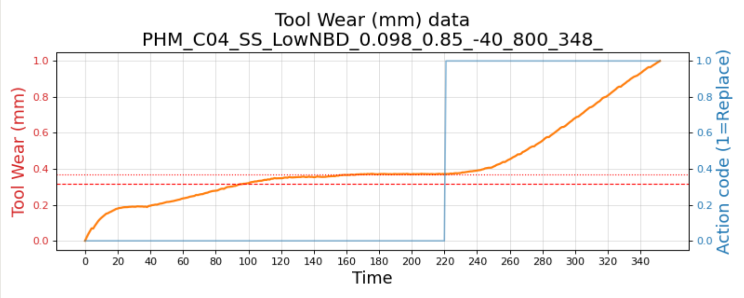
1. Simulated. Based on Dašić (2006). Simple single-variate state (tool wear)
   - Variants: (1) No noise (2) Low noise and low break-down chance and (3) High noise and high break-down chance

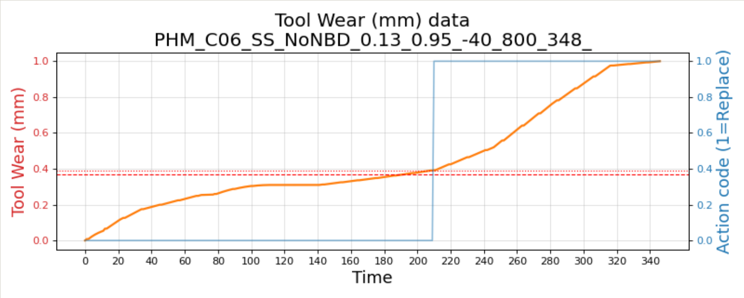
2. PHM 2010 real data – Simple single-variate state (tool wear)
   - Variants: C-01, C-04 and C-06 data-sets
   - Variants: (1) No noise (2) Low noise and low break-down chance and (3) High noise and high break-down chance

3. PHM 2010 real data – Complex multivariate state (tool wear, 3-axis forces, 3-axis vibration and acoustic data)
   - Variants: C-01, C-04 and C-06 data-sets

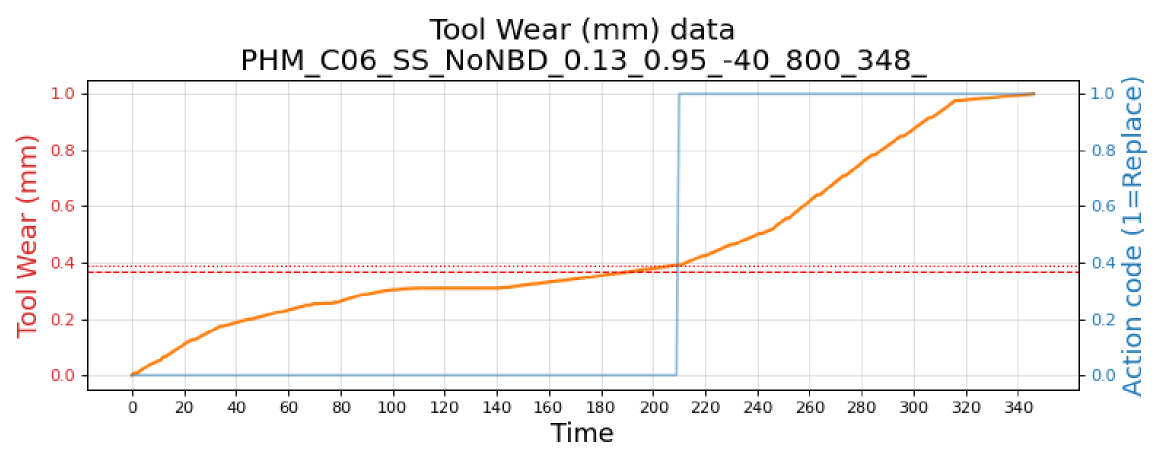


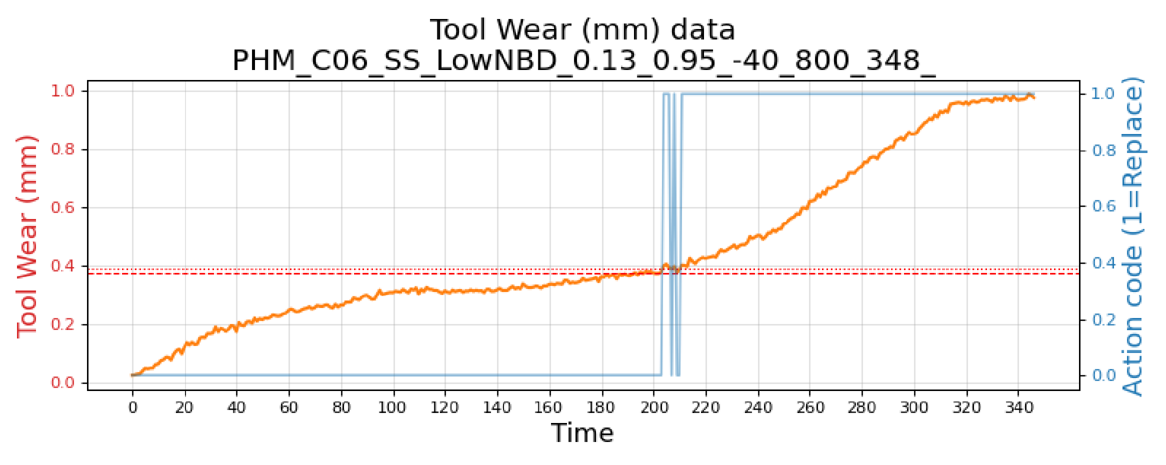



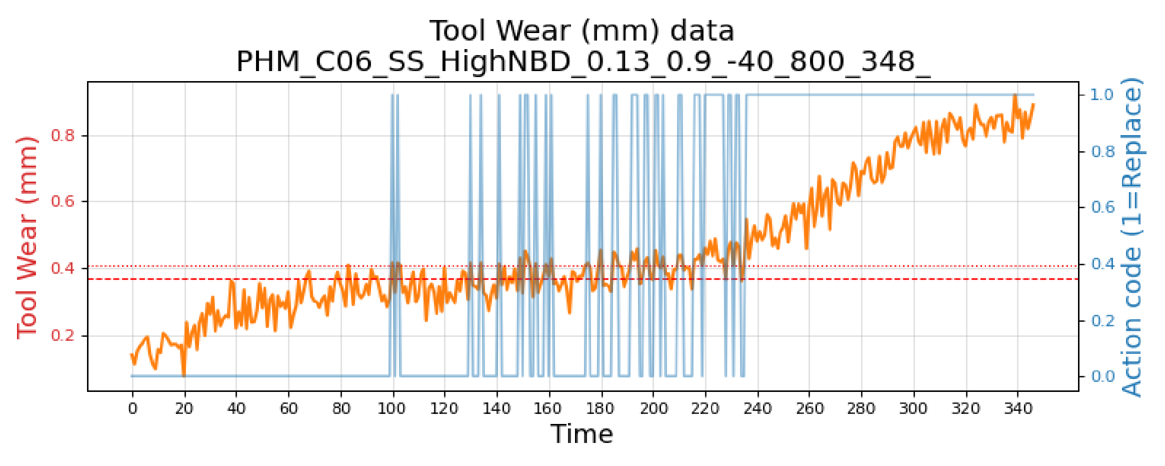



# Wear plot - real data (PHM C06) and its variants




PHM 2010 C-06 data-set

- No noise, no break-down chance
- Low noise: 1e-3 and break-down chance 5%
- High noise: 1e-2 and break-down chance 10%

# Evaluation strategy

- RL policy decides when to replace tool
- Compare against “human” preventive replacement policy
- REINFORCE trained for 800 episodes. SB-3 trained with 10,000 episodes
- Train over 10 rounds to understand training stability
- Evaluate: During each round, test from another test set, randomly sampled 40 points, and tested over 10 rounds
- Compute Precision, Recall and F1, F1-Beta
- Compare mean and std. deviations

# Findings and Results

# Findings

1. The naïve implementation of REINFORCE algorithm was implemented in PyTorch with an extremely simple architecture: One hidden layer and ReLU activation and an Adam optimizer.
2. Despite its simplicity, REINFORCE performs significantly better than the three advanced algorithms.

Average across 10 trained models, across all variants:

1. Precision: 0.687 against A2C: 0.449, DQN: 0.418, PPO: <u>0.472</u>
2. F1-score:  0.609 against A2C: <u>0.442</u>, DQN: 0.374, PPO: 0.345
3. Variability: Precision and F1 lower by 0.08 and 0.016, when compared to the average of A2C, DQN, PPO

"Best" model from the 10, across all variants:

1. Precision: 0.884 against A2C: 0.520, DQN: <u>0.651</u>, PPO: 0.558
2. F1-score : 0.873 against A2C: 0.639, DQN: <u>0.740</u>, PPO: 0.580

# Results: Overall – all environments and their variants

**Overall:**

(1) Simulated x 3 with noise levels

(2) PHM Real-data: Uni-variate state x 3 data sets x 3 noise levels

(3) PHM Real-data: Multi-variate state x 3 data sets

| | **Precision** | | **Recall** | | **F1 score** | | **F Beta (0.5)** | |
|---|---|---|---|---|---|---|---|---|
| | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ |
| 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** |

# Results: Simple single variate state. Including noise variants

**Simulated – Dašić, Predrag (2006).**

| | Precision | | Recall | | F1 score | | F Beta (0.5) | |
|---|---|---|---|---|---|---|---|---|
| | μ | σ | μ | σ | μ | σ | μ | σ |
| 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** |

**PHM 2010: Single-variate environment**, across three data sets C-01, C-04 and C-06

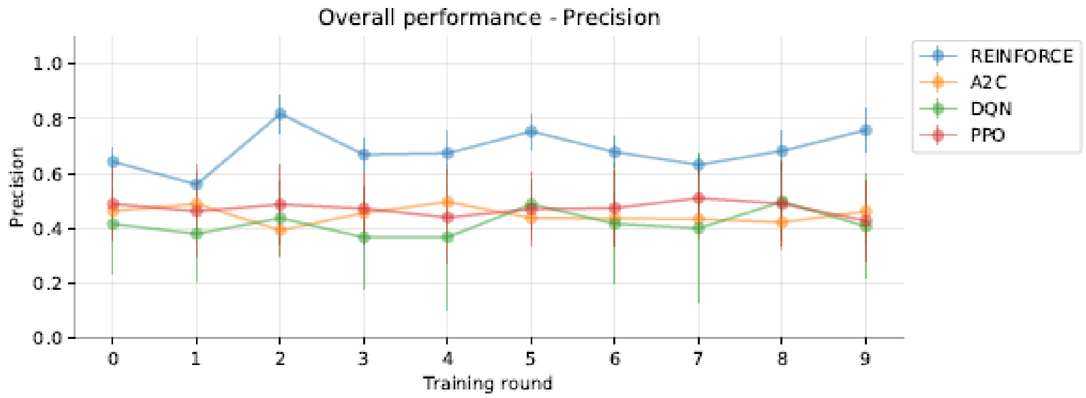
| | Precision | | Recall | | F1 score | | F Beta (0.5) | |
|---|---|---|---|---|---|---|---|---|
| | μ | σ | μ | σ | μ | σ | μ | σ |
| A2C | 0.447 | 0.077 | 0.477 | 0.091 | 0.452 | 0.072 | 0.446 | 0.070 |
| DQN | 0.419 | 0.179 | 0.507 | 0.032 | 0.379 | 0.036 | 0.352 | 0.057 |
| PPO | 0.450 | 0.146 | 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** |

# Results: Complex, multi-variate environment

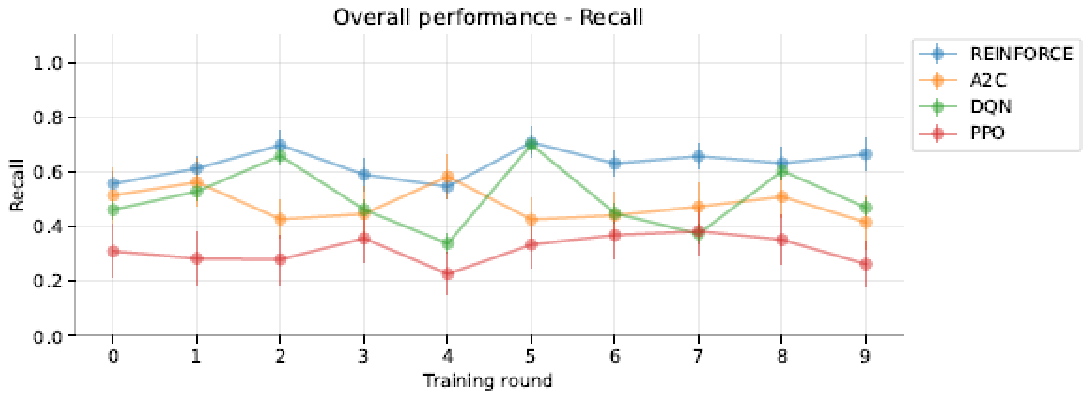
**PHM 2010: Complex, multi-variate environment**, across three data sets C-01, C-04 and C-06
No noise or break-down

| | Precision | | Recall | | F1 score | | F Beta (0.5) | |
|---|---|---|---|---|---|---|---|---|
| | μ | σ | μ | σ | μ | σ | μ | σ |
| 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** |

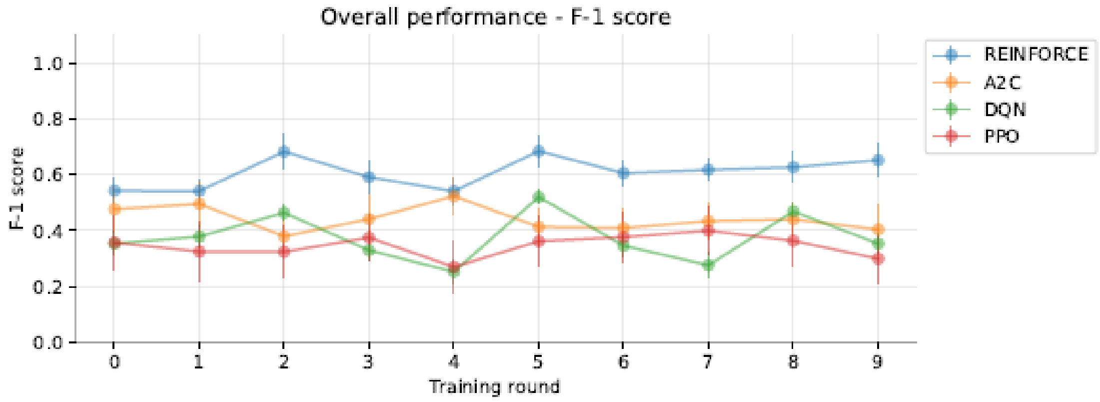
# Results: Overall – Training across 10 rounds



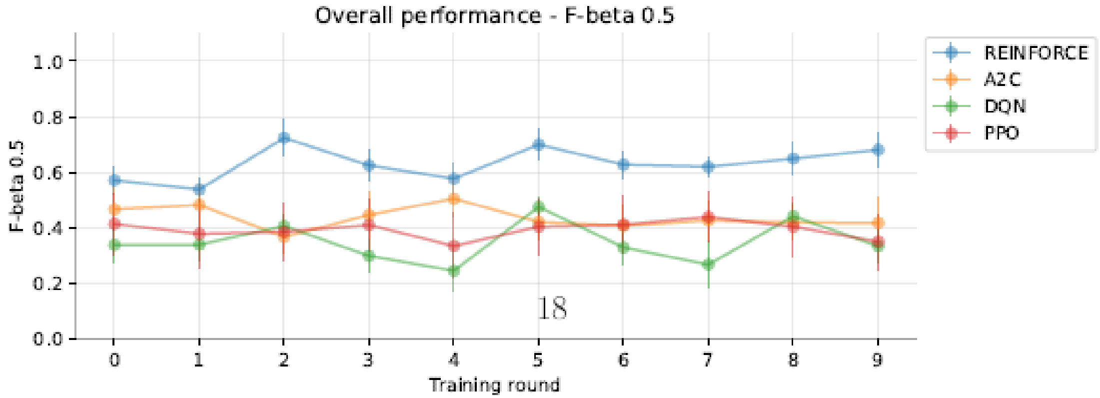
(a) Precision



(b) Recall

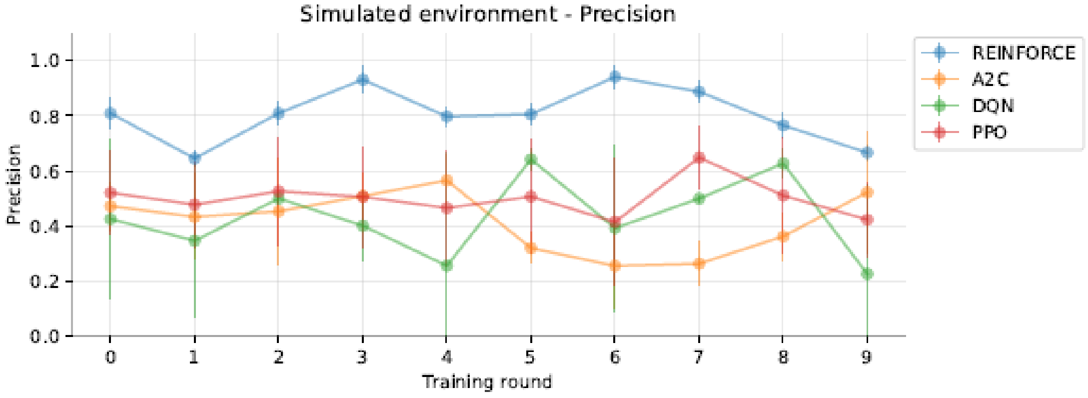


(c) F1-score

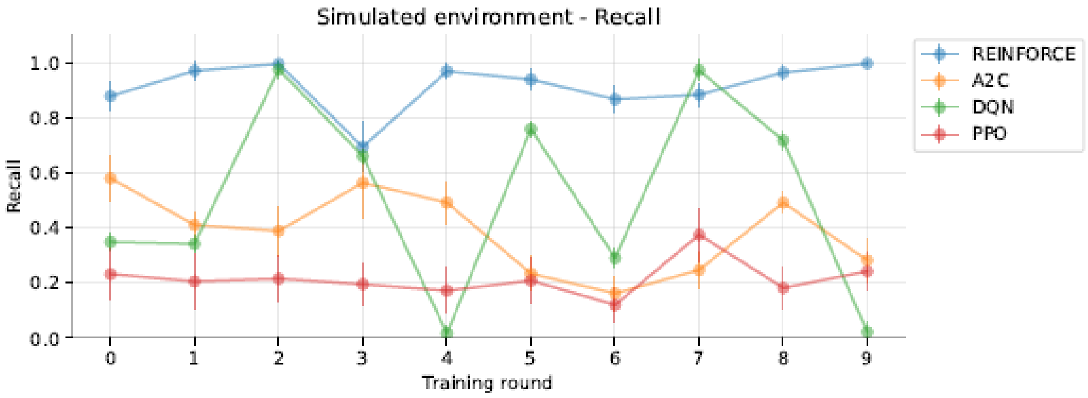


(d) F1-beta (0.5)

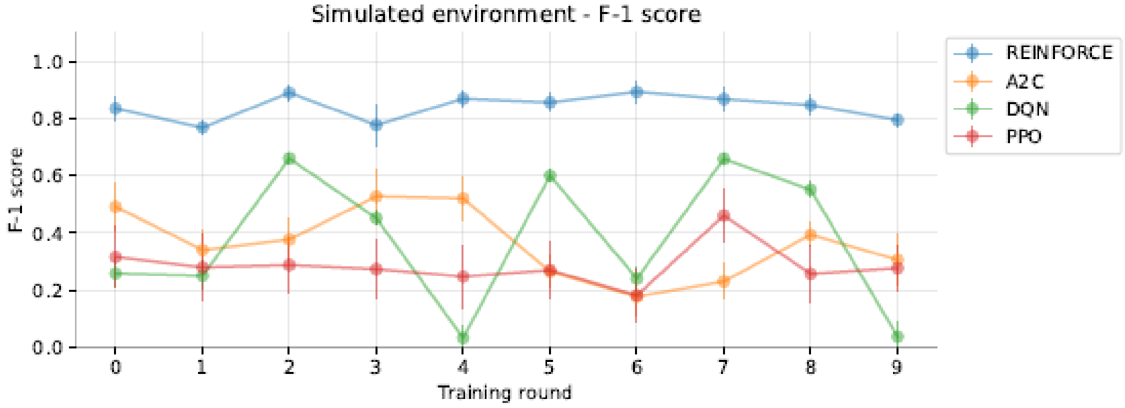
# Results: Simulated – Training across 10 rounds



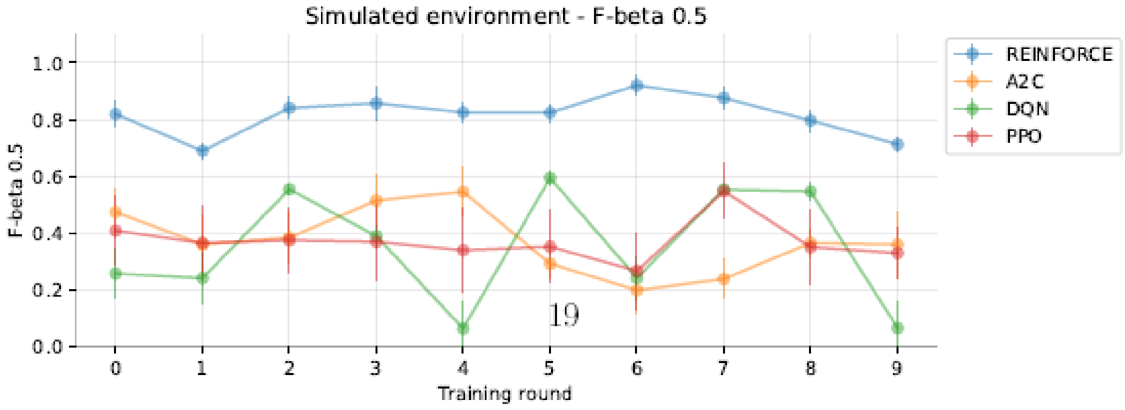

(a) Precision




(b) Recall

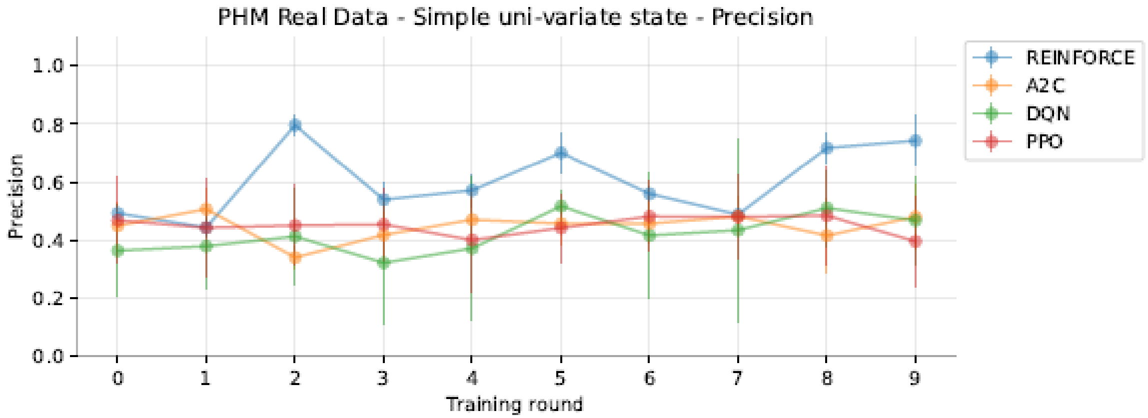



(c) F1-score

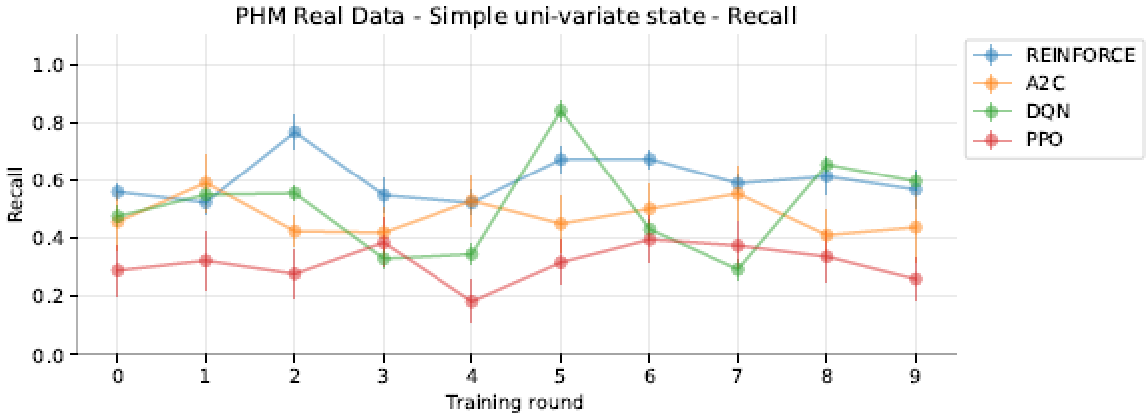



(d) F1-beta (0.5)

# Results: PHM Real Data – **3** data-sets - Simple univariate

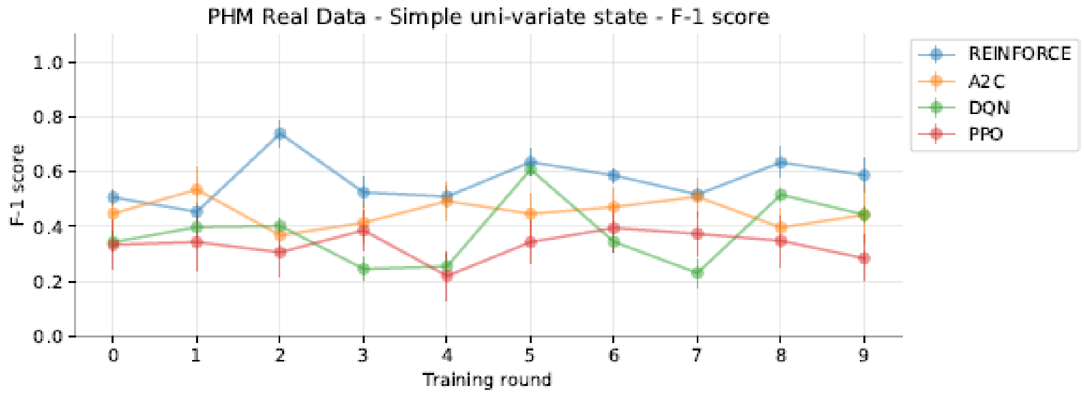



(a) Precision

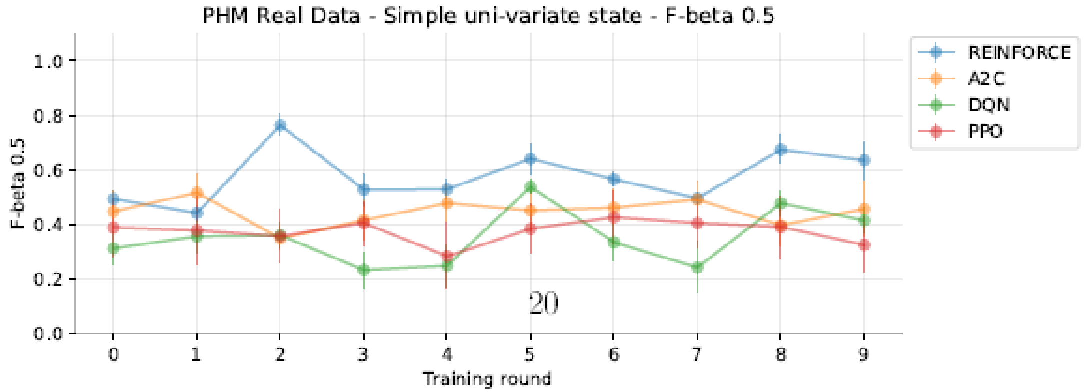



(b) Recall

(b) Recall

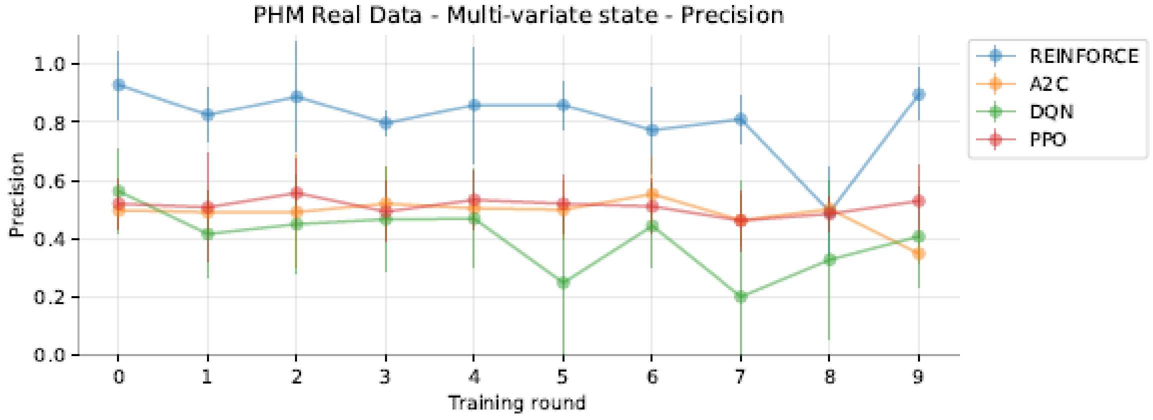



(c) F1-score

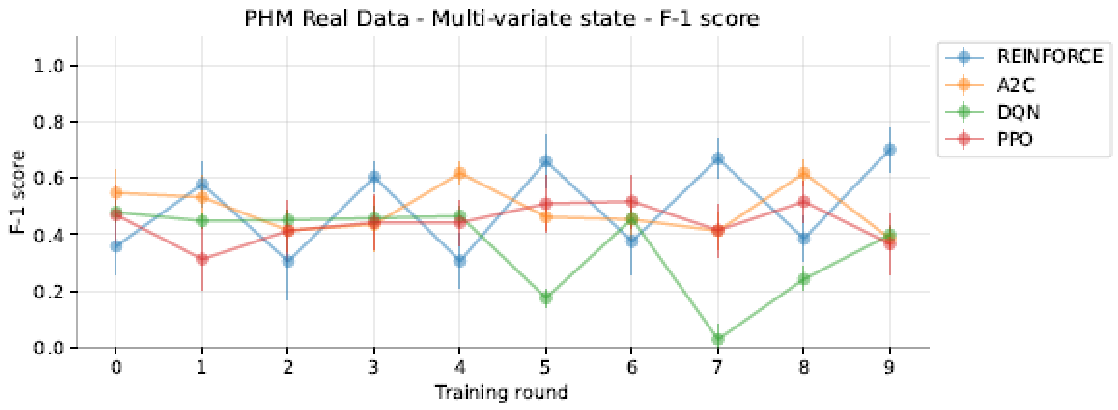



(d) F1-beta (0.5)

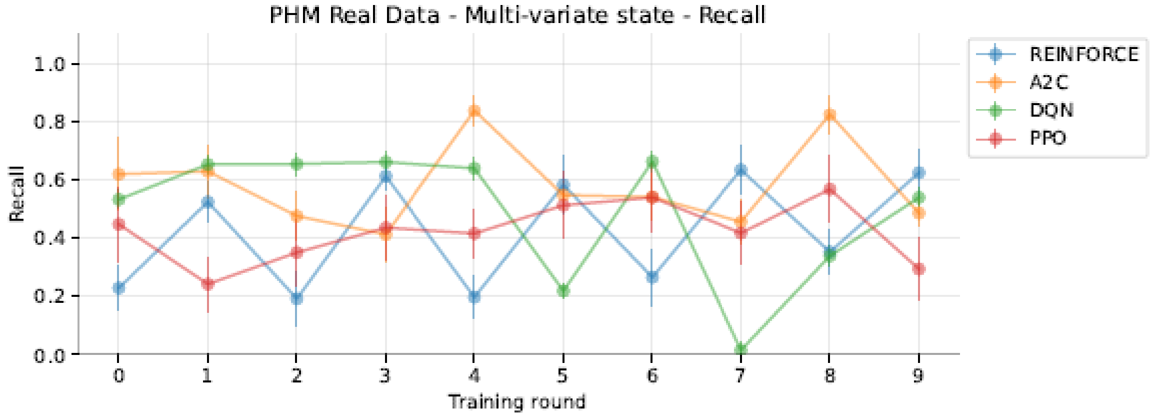
# Results: PHM Real Data – **3** data-sets – Multi-variate



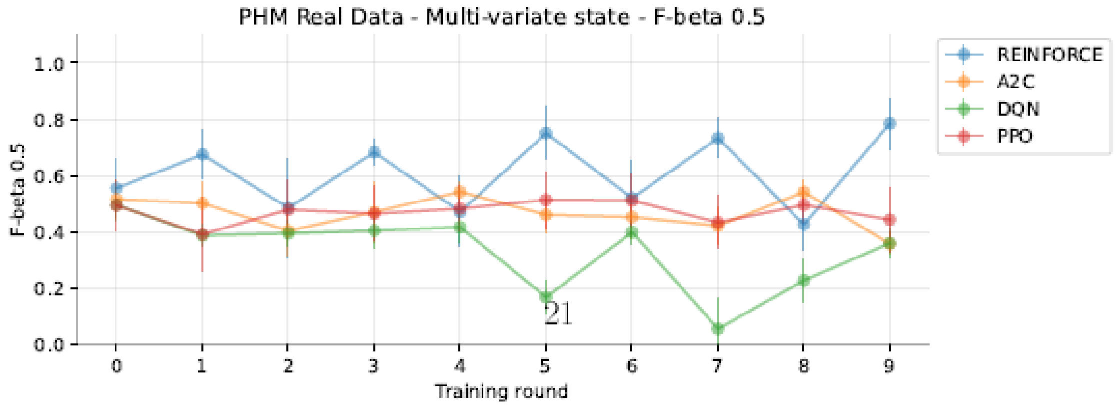

(a) Precision




(c) F1-score




(b) Recall




(d) F1-beta (0.5)

# Statistical validation: Two sample, one-tail test

Two sample, one-tail test

$\alpha$ = 0.05, 95% confidence

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

## Average metric

| | REINFORCE | A2C | DQN | PPO |
|---|---|---|---|---|
| **Overall** | | | | |
| Precision | 0.687 | 0.449 | 0.418 | 0.472 |
| Recall | 0.629 | 0.480 | 0.504 | 0.316 |
| F_1_Score | 0.609 | 0.442 | 0.374 | 0.345 |
| **Simulated** | | | | |
| Precision | 0.806 | 0.415 | 0.431 | 0.500 |
| Recall | 0.915 | 0.385 | 0.510 | 0.215 |
| F_1_Score | 0.841 | 0.363 | 0.374 | 0.284 |
| **PHM-SS** | | | | |
| Precision | 0.605 | 0.447 | 0.419 | 0.450 |
| Recall | 0.603 | 0.477 | 0.507 | 0.314 |
| F_1_Score | 0.570 | 0.452 | 0.379 | 0.333 |
| **PHM-MS** | | | | |
| Precision | 0.813 | 0.487 | 0.399 | 0.511 |
| Recall | 0.421 | 0.582 | 0.491 | 0.422 |
| F_1_Score | 0.495 | 0.488 | 0.360 | 0.441 |

## p values

| | Samples | A2C | DQN | PPO |
|---|---|---|---|---|
| **Overall** | 1500 | | | |
| Precision | | 4.31E-126 | 2.17E-109 | 2.81E-106 |
| Recall | | 4.20E-35 | 3.37E-16 | 4.36E-150 |
| F_1_Score | | 1.99E-64 | 1.46E-88 | 5.29E-155 |
| **Simulated** | 300 | | | |
| Precision | | 3.20E-98 | 1.69E-63 | 2.65E-81 |
| Recall | | 8.12E-104 | 2.56E-41 | 1.57E-264 |
| F_1_Score | | 9.60E-134 | 8.56E-99 | 2.96E-242 |
| **PHM-SS** | 900 | | | |
| Precision | | 2.27E-32 | 7.29E-31 | 9.95E-31 |
| Recall | | 1.27E-16 | 1.55E-06 | 8.19E-71 |
| F_1_Score | | 1.94E-19 | 4.67E-34 | 2.19E-67 |
| **PHM-MS** | 300 | | | |
| Precision | | 1.64E-60 | 3.34E-54 | 7.88E-59 |
| Recall | | 2.69E-10 | 2.69E-02 | 9.68E-01 |
| F_1_Score | | 7.27E-01 | 1.44E-08 | 1.35E-03 |

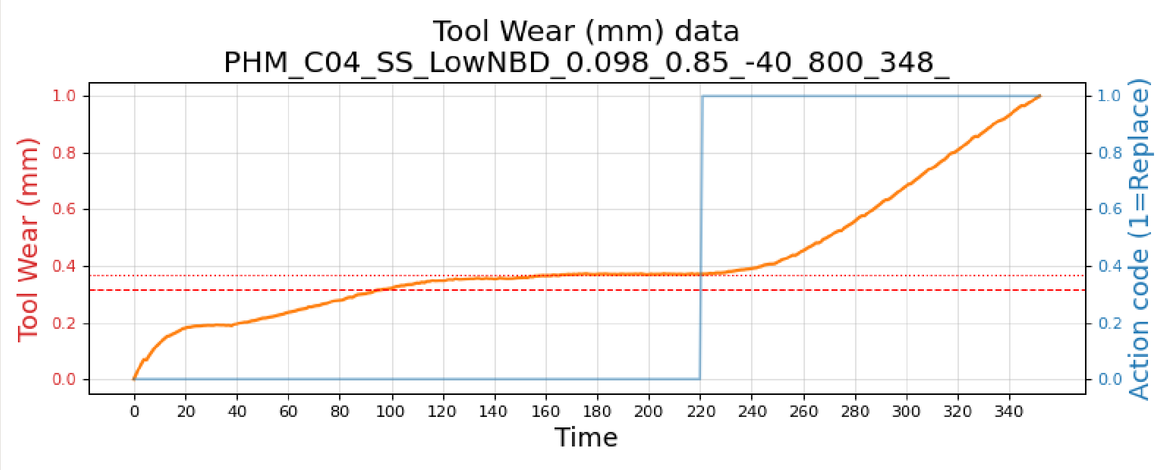
## t statistic

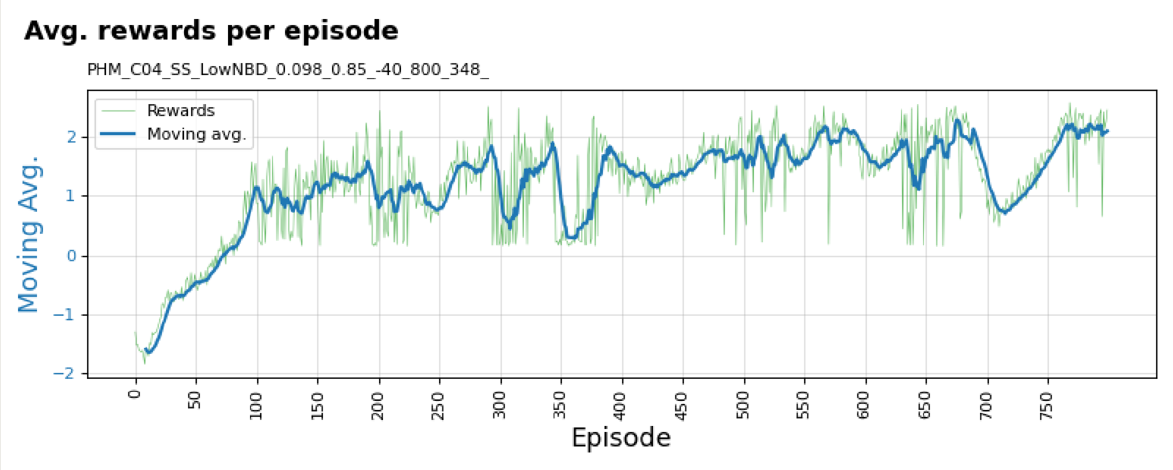
| | A2C | DQN | PPO |
|---|---|---|---|
| **Overall** | | | |
| Precision | 25.071 | 23.170 | 22.804 |
| Recall | 12.522 | 8.206 | 27.650 |
| F_1_Score | 17.364 | 20.634 | 28.160 |
| **Simulated** | | | |
| Precision | 25.611 | 19.032 | 22.427 |
| Recall | 26.665 | 14.558 | 62.541 |
| F_1_Score | 32.402 | 25.719 | 56.575 |
| **PHM-SS** | | | |
| Precision | 12.082 | 11.770 | 11.742 |
| Recall | 8.357 | 4.821 | 18.607 |
| F_1_Score | 9.121 | 12.423 | 18.098 |
| **PHM-MS** | | | |
| Precision | 18.451 | 17.207 | 18.122 |
| Recall | -6.425 | -2.219 | -0.041 |
| F_1_Score | 0.349 | 5.748 | 3.220 |

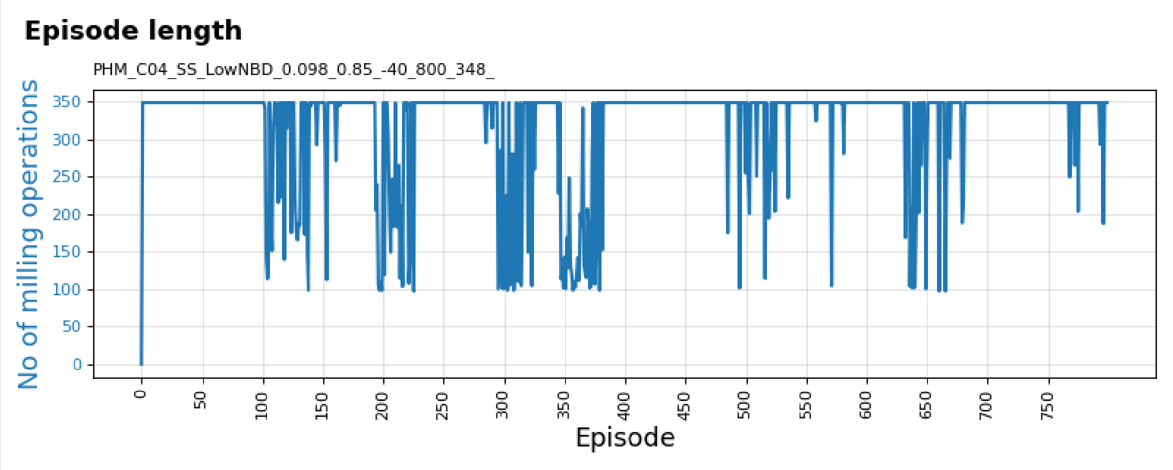
# Some plots

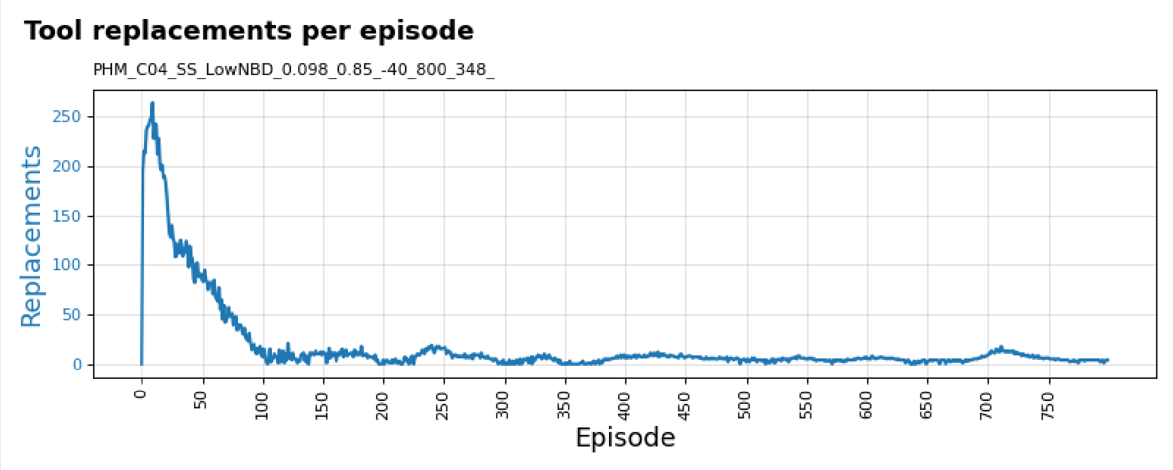
# Training plots for REINFORCE algorithm

PHM 2010 C-04 data-set: Variant: Single-state tool-wear with low noise (1e-3) and low break-down chance (5%)



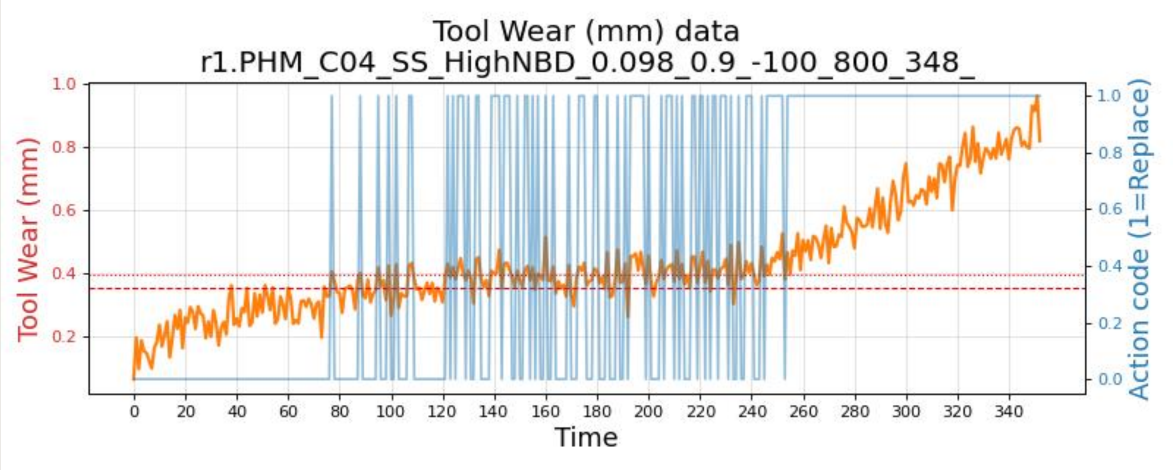



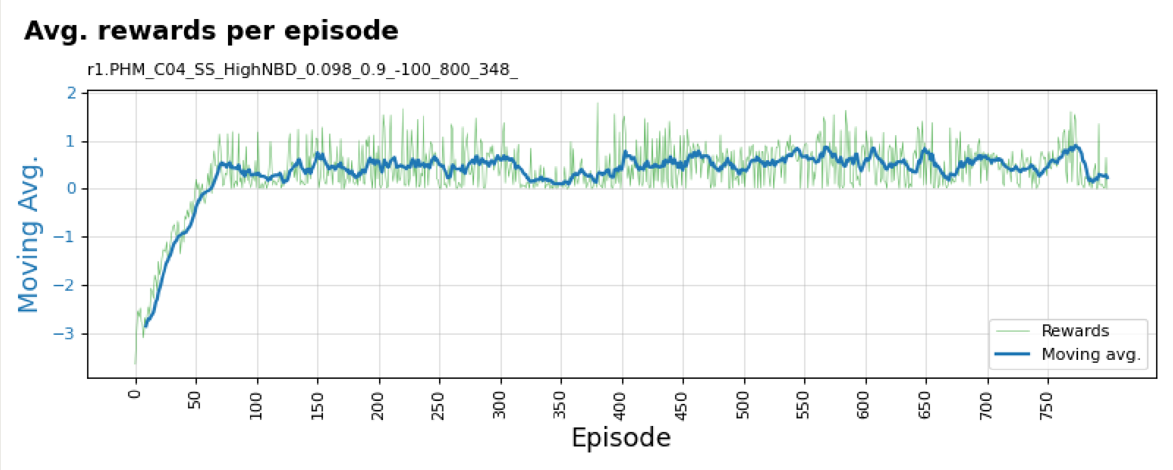



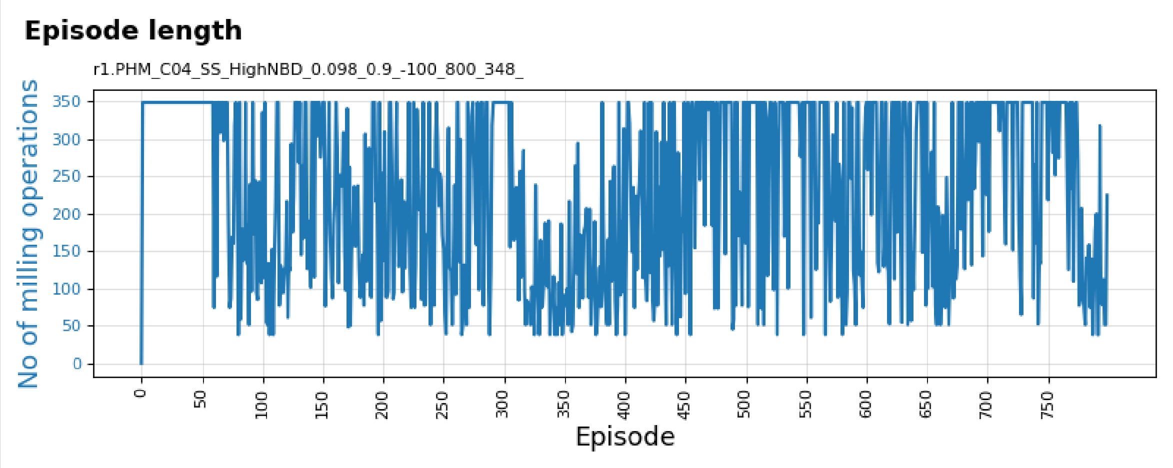



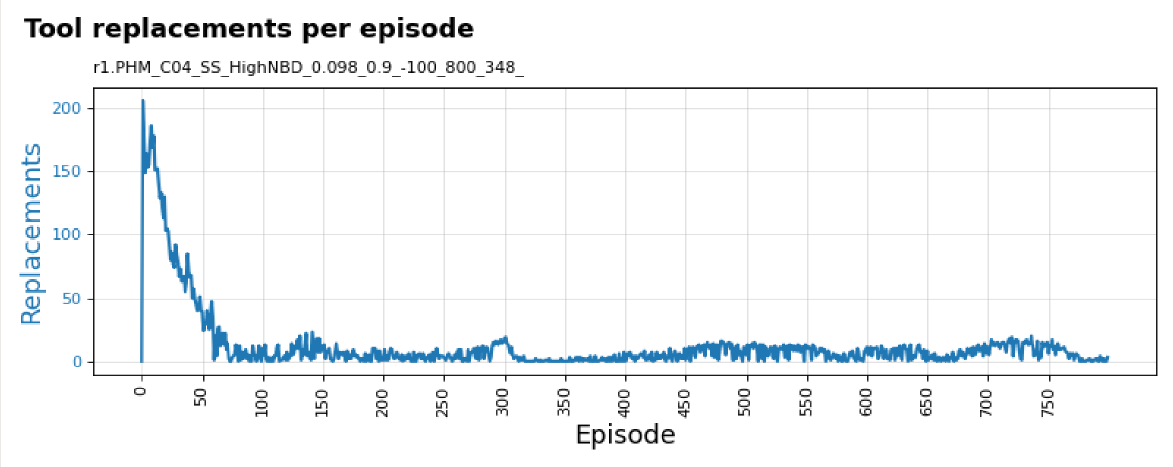
# Training plots for REINFORCE algorithm

PHM 2010 C-04 data-set: Variant: Single-state tool-wear with high noise (1e-2) and low break-down chance (10%)



# Thank you