Experiments with REINFORCE algorithm

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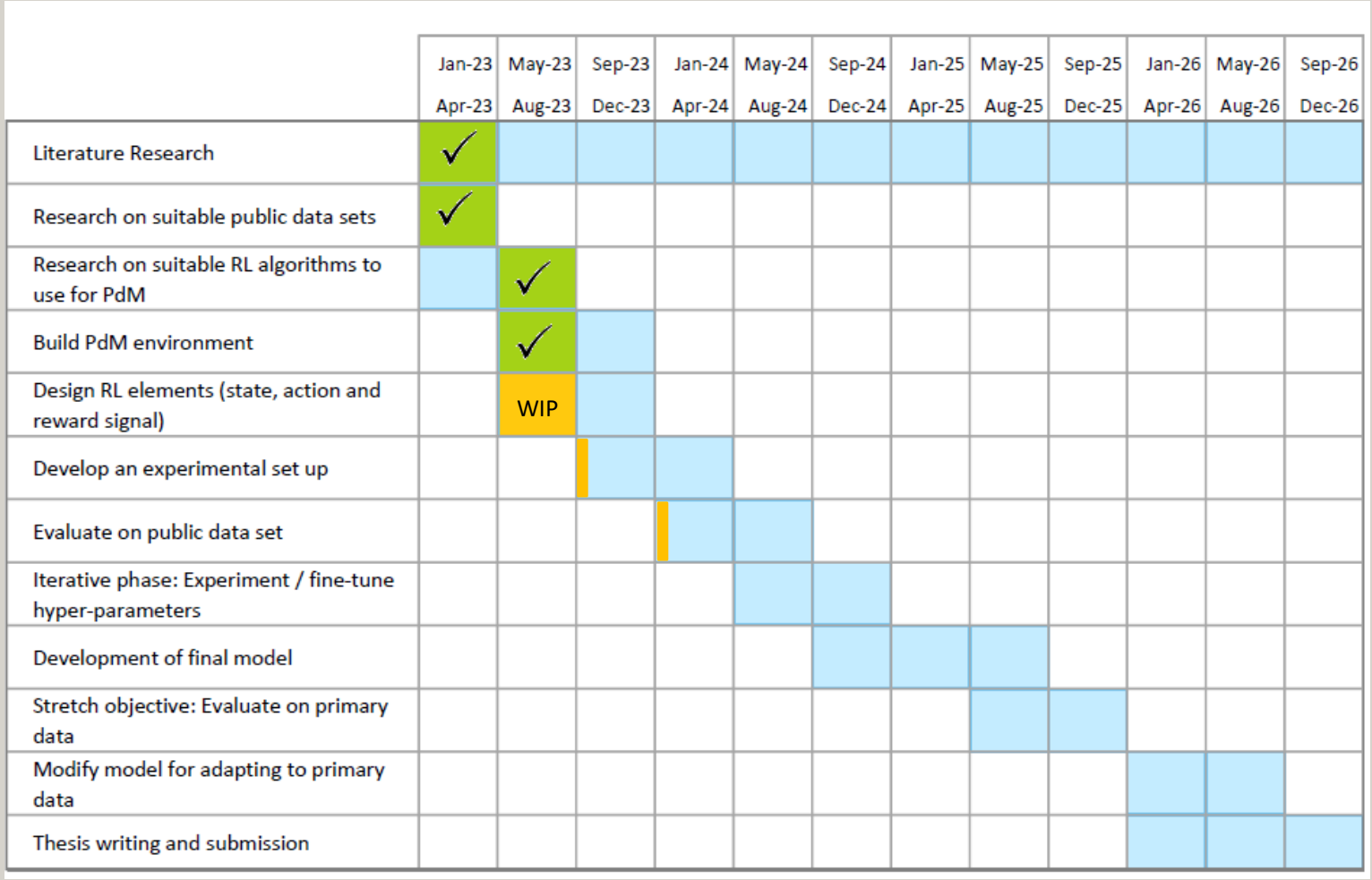
Planned schedule and status

OBJECTIVES:

1. Evaluate various RL algorithms suitable for solving predictive maintenance (PdM)
2. Design and develop a PdM application with above recommendation.
3. Extract features and explore techniques for standardizing the features across various applications.
4. To develop a data-driven model on real world data set

Current status:

1. SLR paper published in Q1 journal
2. Obj. 1: Empirical study on 4 RL algorithms completed



Agenda

1. Objective ▶
2. The RL environment ▶
3. Evaluation strategy ▶
4. Findings ▶
5. Results, Plots, Tests ▶

Objectives

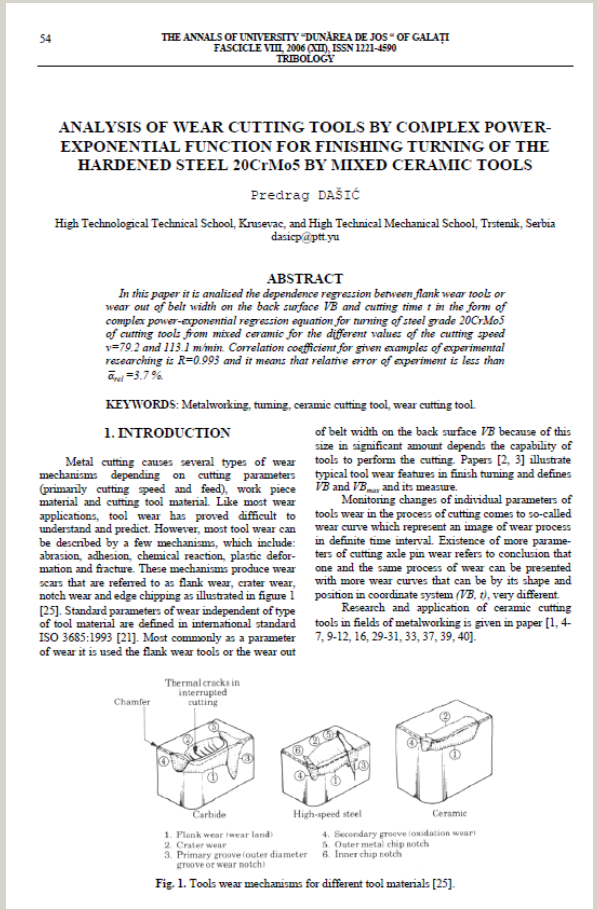
Research goal*: An optimal predictive maintenance policy for replacement of milling tool

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

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



54 THE ANNALS OF UNIVERSITY "DUNĂREA DE JOS" OF GALAȚI
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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

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ABSTRACT

In this paper it is analized 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 $\bar{\varepsilon}_{rel}$ =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

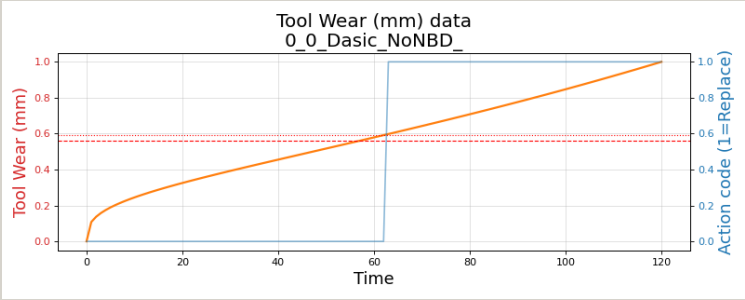
RL environment - Variants

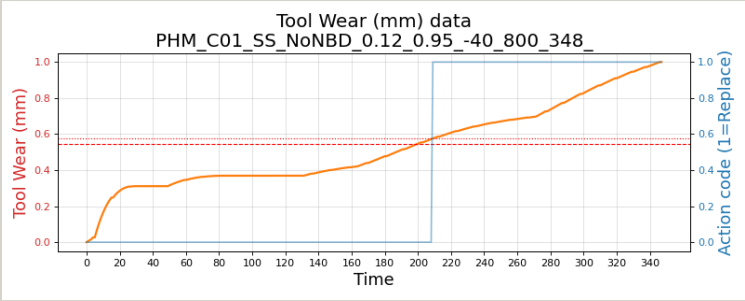
Three environments and their variants:

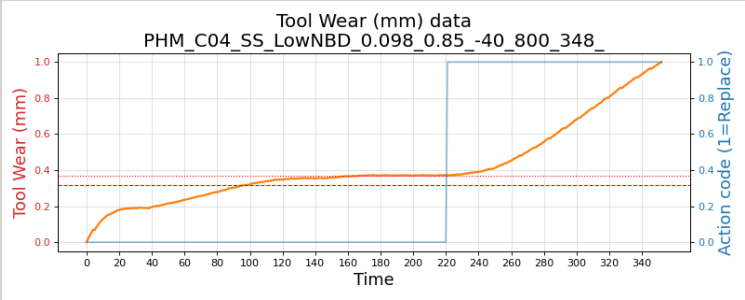
1. Simulated. Based on Dašić (2006). Simple single-variate state (tool wear)
    - Variants: (1) No noise (2) Low noise and low break-down chance and (3) High noise and high break-down chance

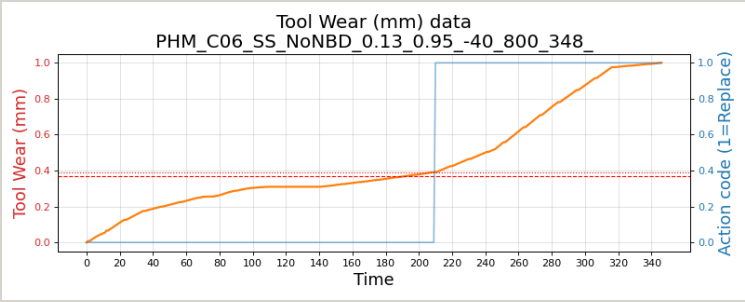
2. PHM 2010 real data – Simple single-variate state (tool wear)
    - Variants: C-01, C-04 and C-06 data-sets
    - Variants: (1) No noise (2) Low noise and low break-down chance and (3) High noise and high break-down chance

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

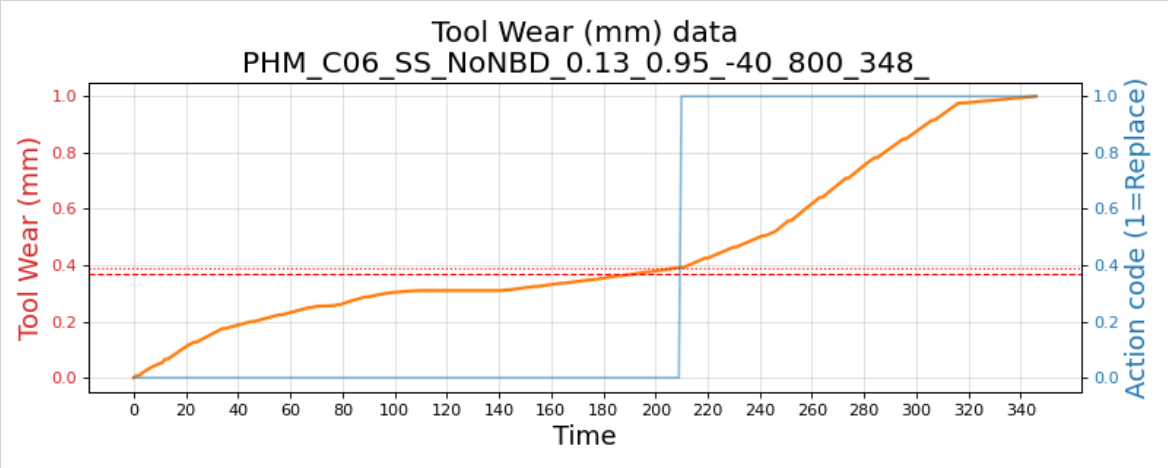


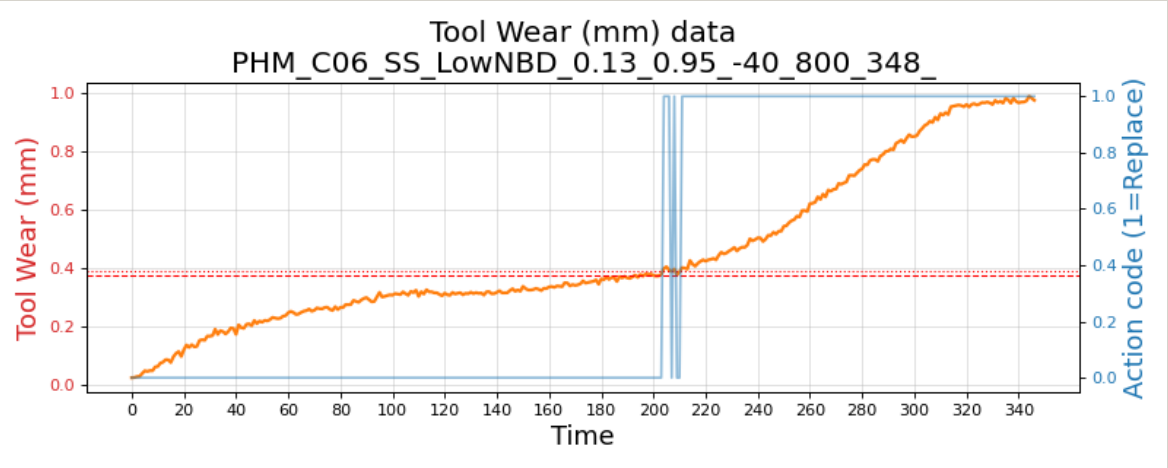


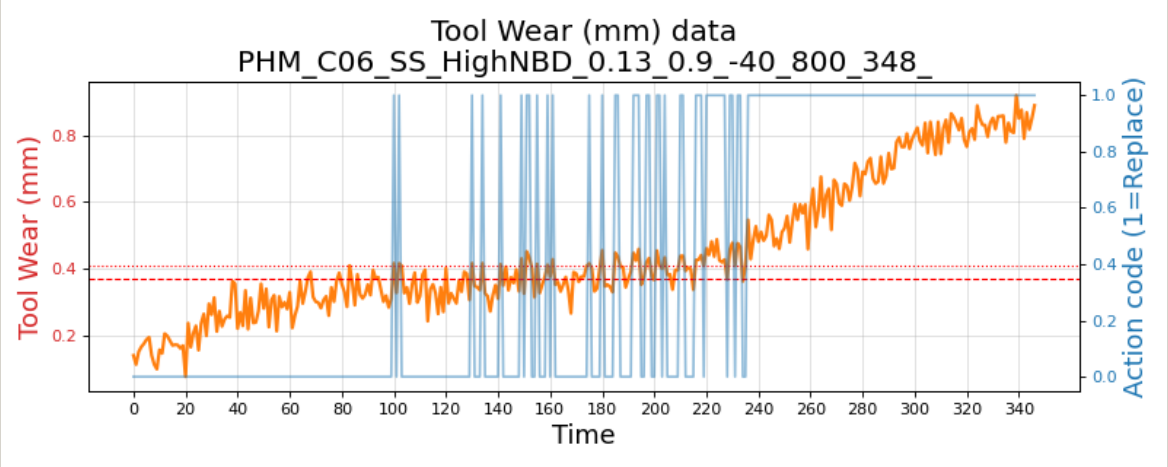




Wear plot - real data (PHM C06) and its variants







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: 0.472
2. F1-score: 0.609 against A2C: 0.442, 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: 0.651, PPO: 0.558
2. F1-score : 0.873 against A2C: 0.639, DQN: 0.740, 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)	
	μ	σ	μ	σ	μ	σ	μ	σ
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

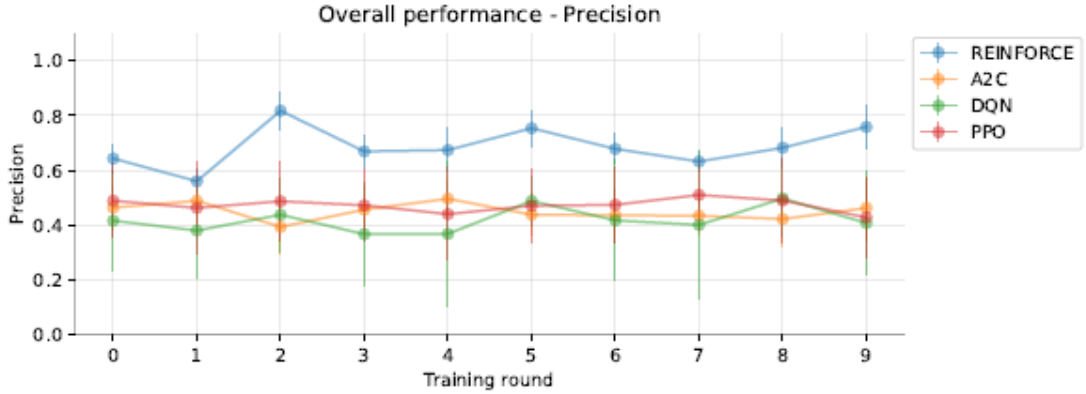
	Precision		Recall		F1 score		F Beta (0.5)	
	μ	σ	μ	σ	μ	σ	μ	σ
A2C	0.447	0.077	0.477	0.091	0.452	0.072	0.446	0.070
DQN	0.419	0.179	0.507	0.032	0.379	0.036	0.352	0.057
PPO	0.450	0.146	0.314	0.082	0.333	0.087	0.374	0.102
REINFORCE	**0.605**	**0.046**	**0.603**	**0.046**	**0.570**	**0.041**	**0.576**	**0.040**

Results: Complex, multi-variate environment

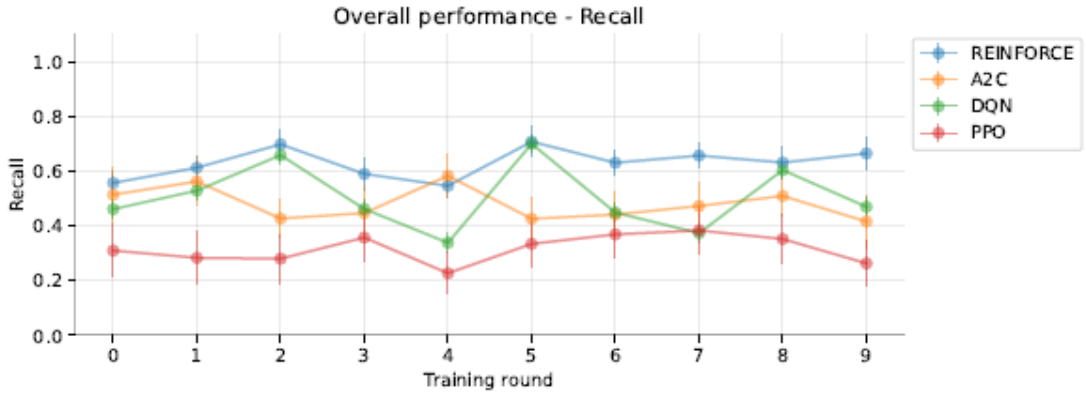
PHM 2010: Complex, multi-variate environment, across three data sets C-01, C-04 and C-06
No noise or break-down

	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**

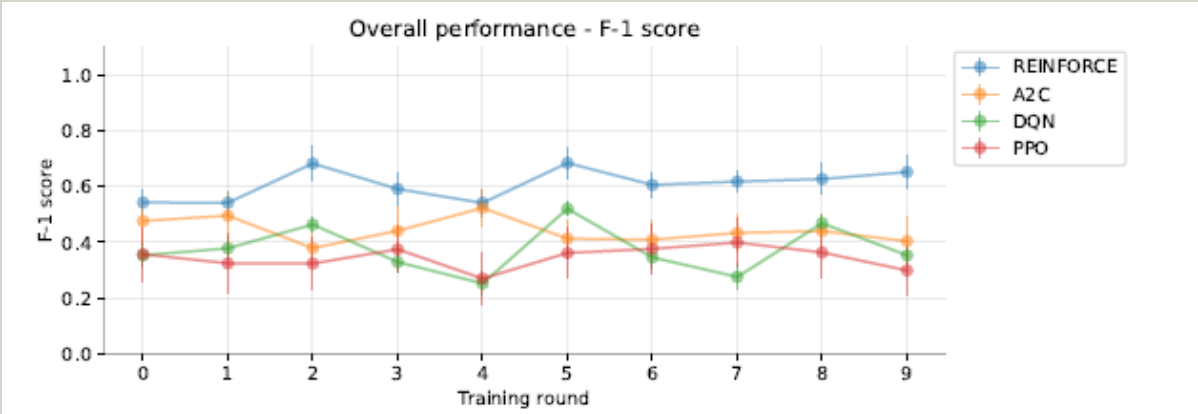
Results: Overall – Training across 10 rounds



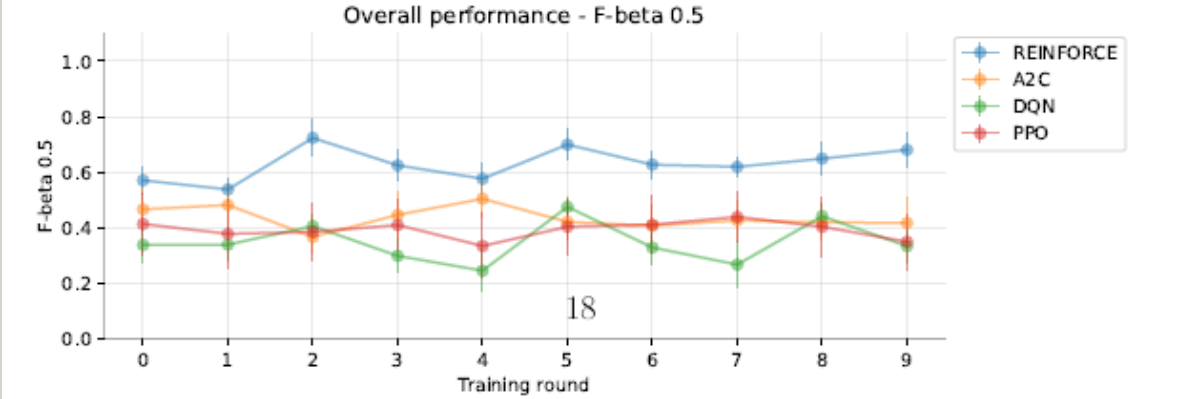
(a) Precision



(b) Recall

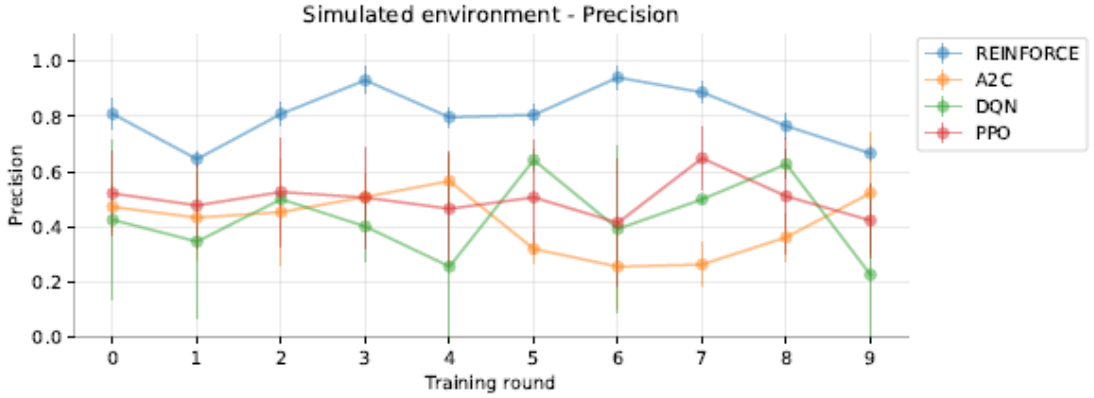


(c) F1-score

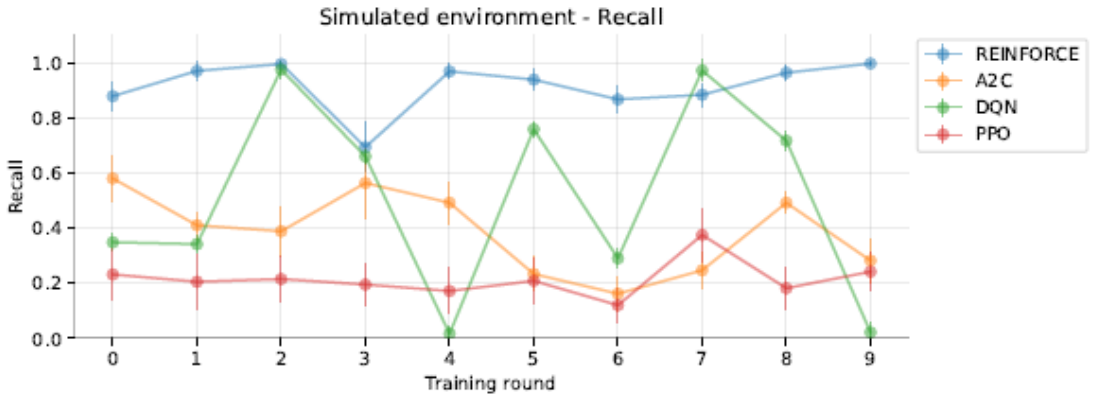


(d) F1-beta (0.5)

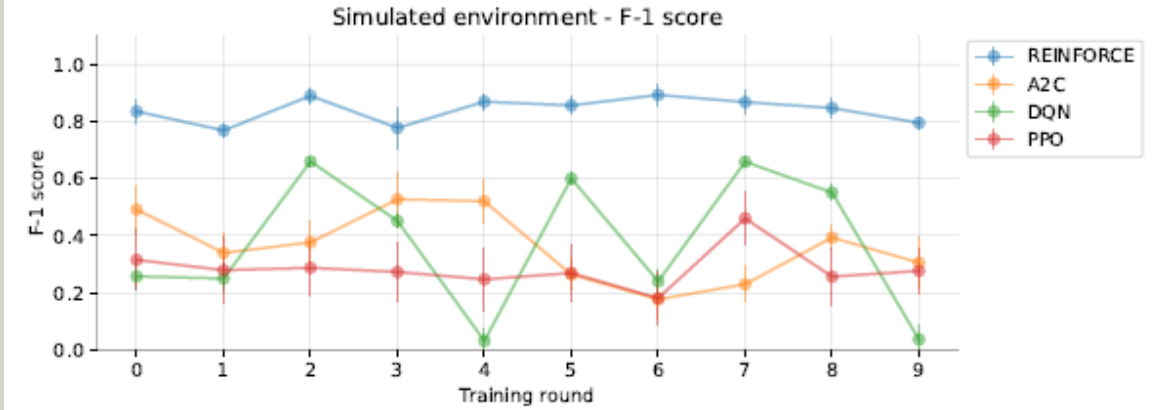
Results: Simulated – Training across 10 rounds



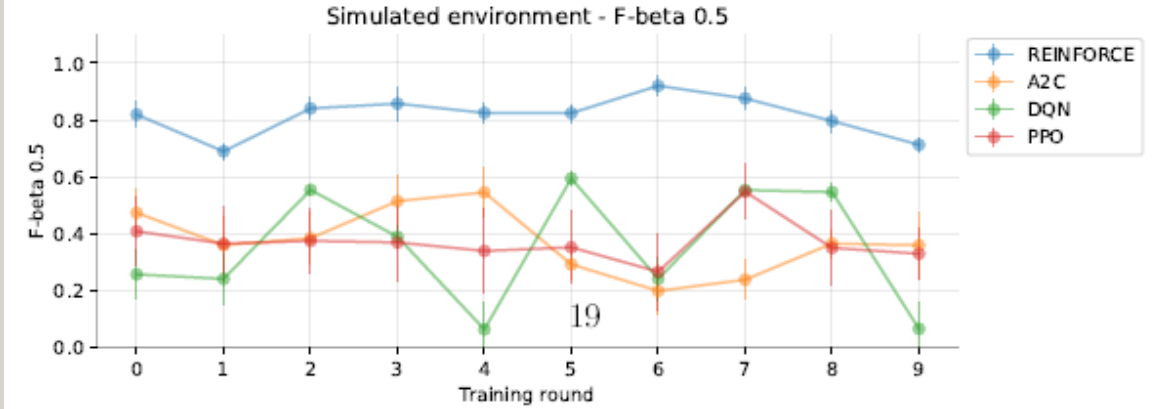
(a) Precision



(b) Recall

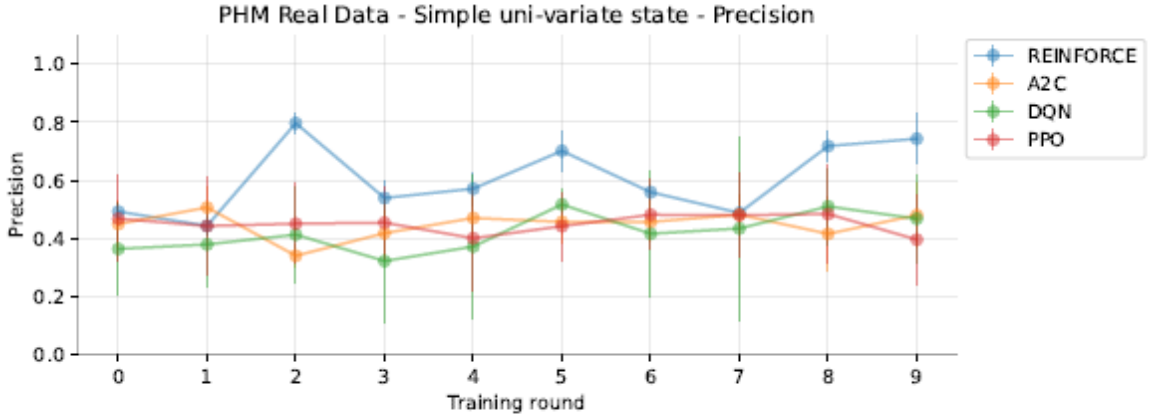


(c) F1-score

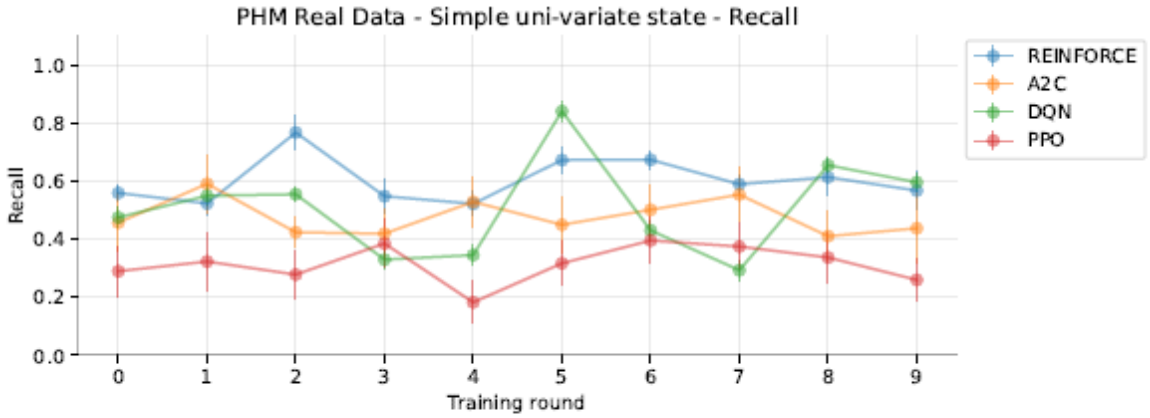


(d) F1-beta (0.5)

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

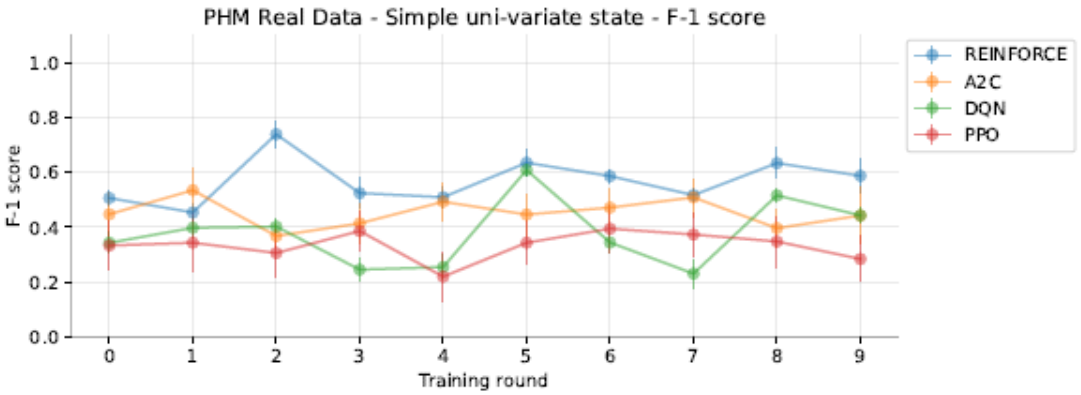


(a) Precision

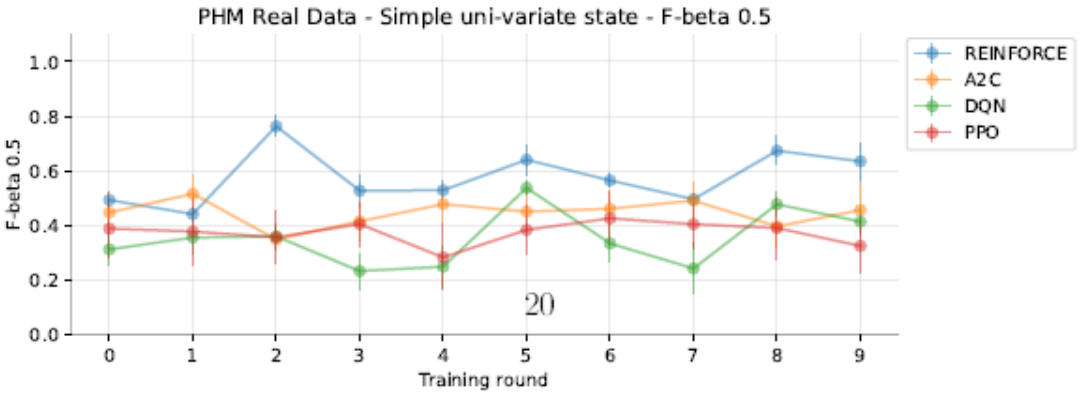


(b) Recall

(b) Recall

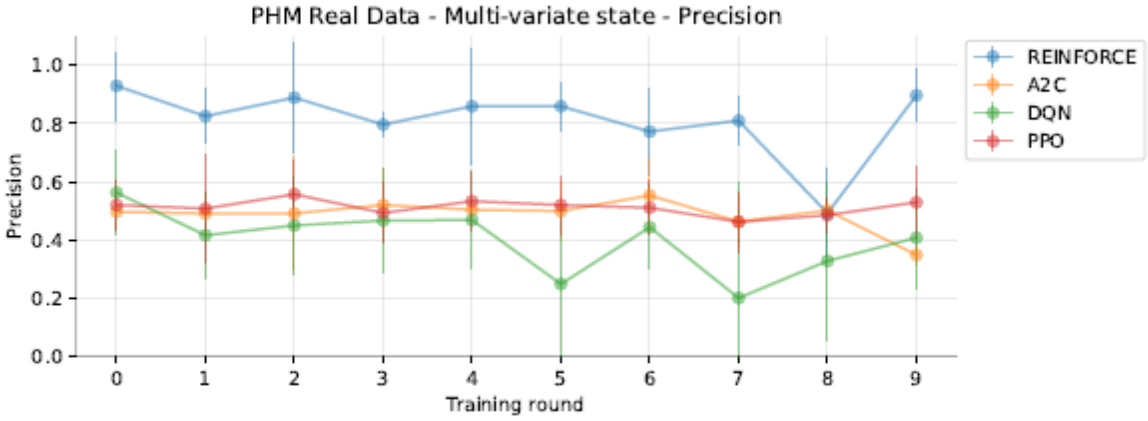


(c) F1-score

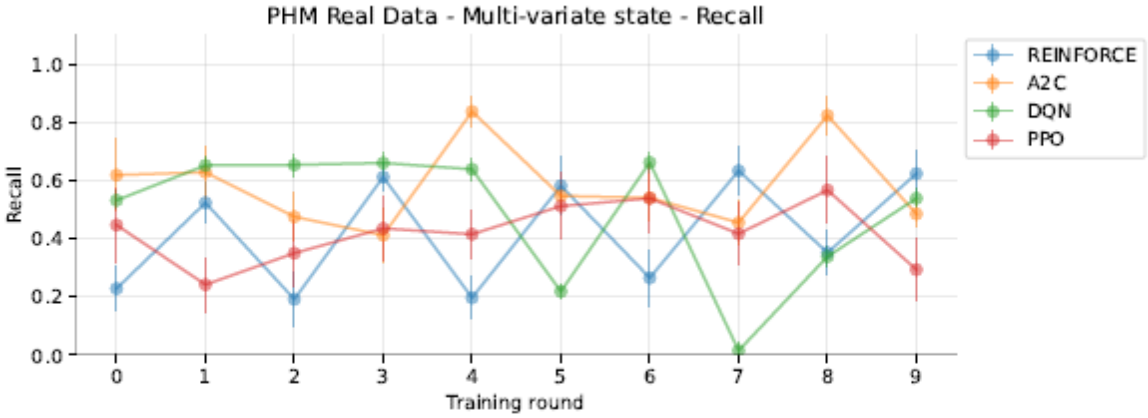


(d) F1-beta (0.5)

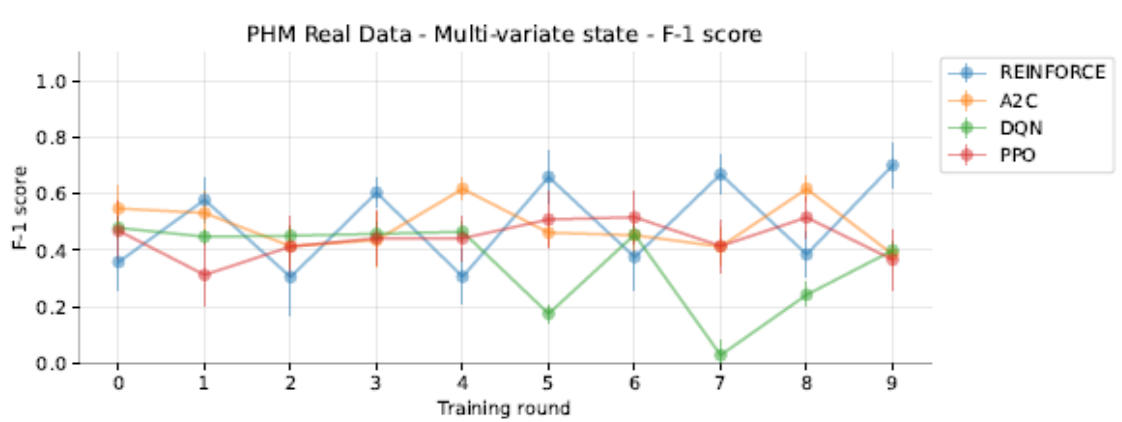
Results: PHM Real Data – **3** data-sets – Multi-variate



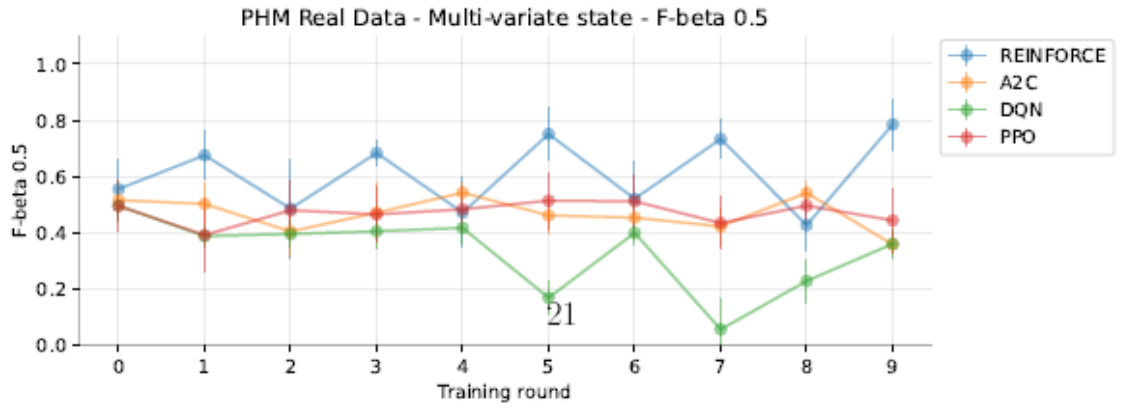
(a) Precision



(b) Recall



(c) F1-score



(d) F1-beta (0.5)

Statistical validation: Two sample, one-tail test

Two sample, one-tail test

α = 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

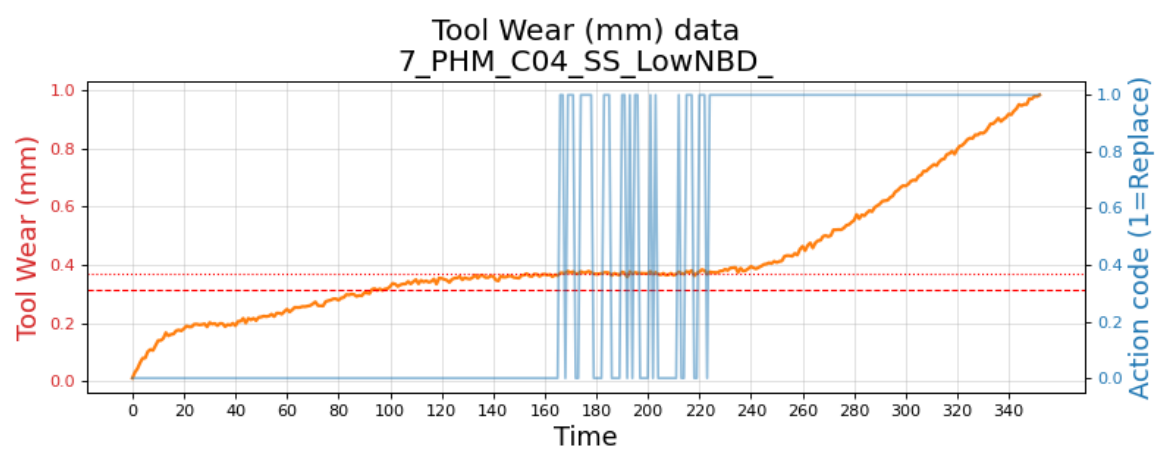
t statistic

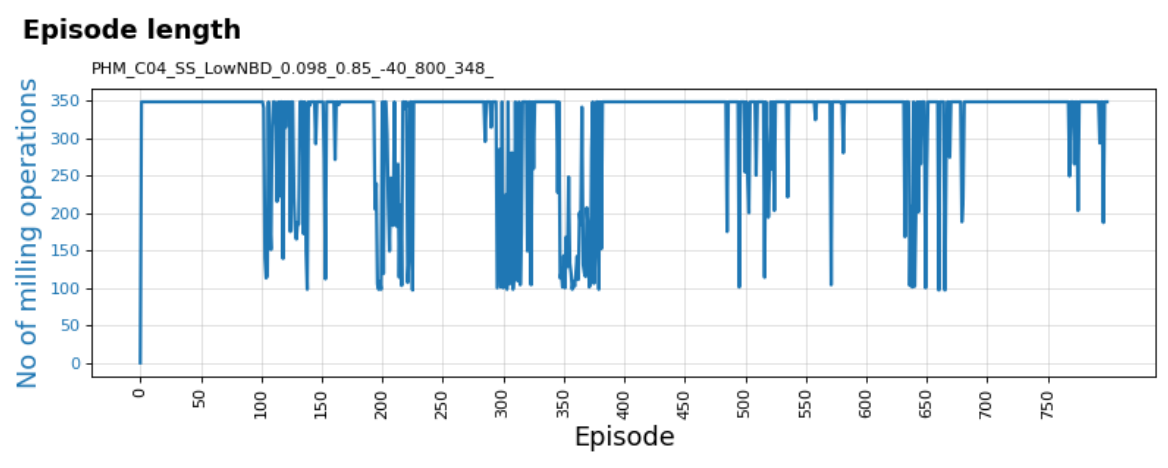
	A2C	DQN	PPO
Overall			
Precision	25.071	23.170	22.804
Recall	12.522	8.206	27.650
F_1_Score	17.364	20.634	28.160
Simulated			
Precision	25.611	19.032	22.427
Recall	26.665	14.558	62.541
F_1_Score	32.402	25.719	56.575
PHM-SS			
Precision	12.082	11.770	11.742
Recall	8.357	4.821	18.607
F_1_Score	9.121	12.423	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

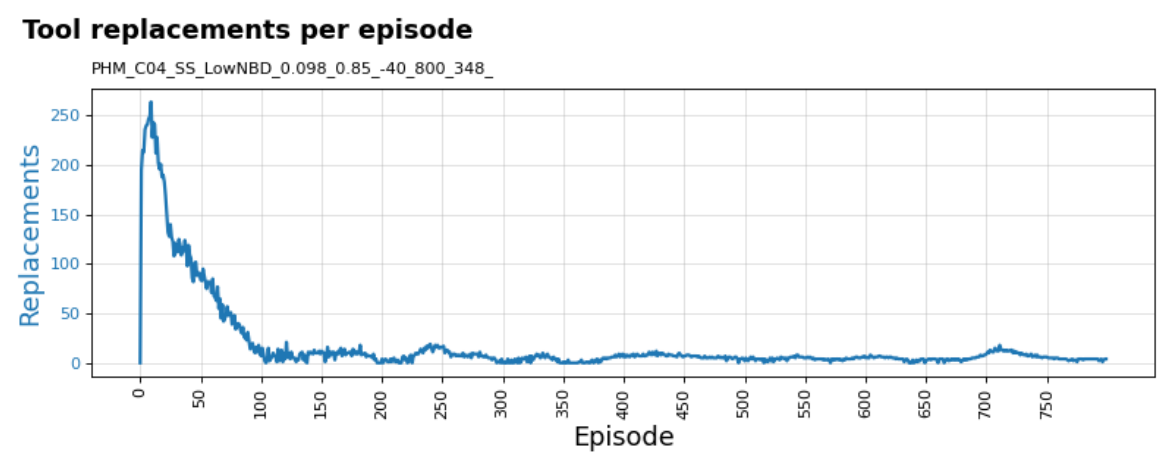
Some plots

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%)

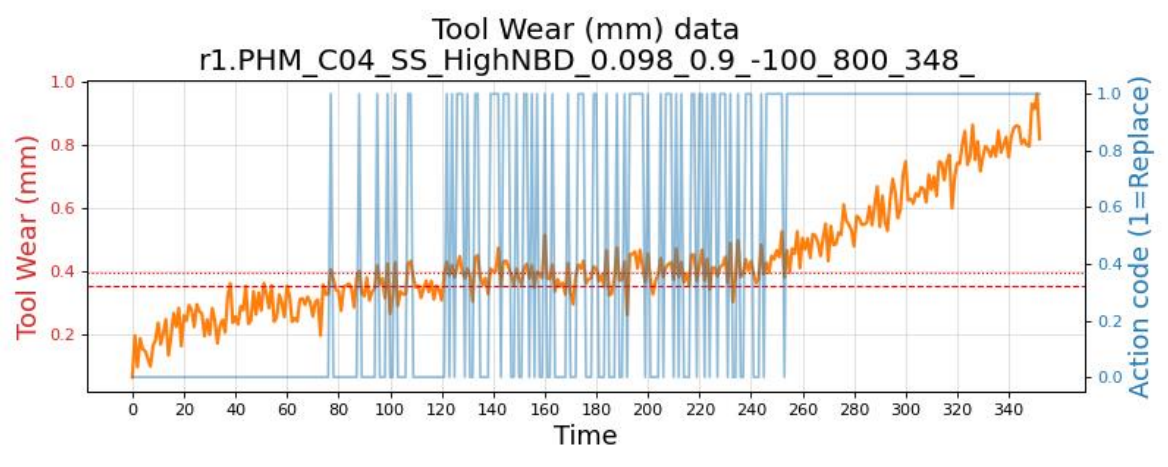


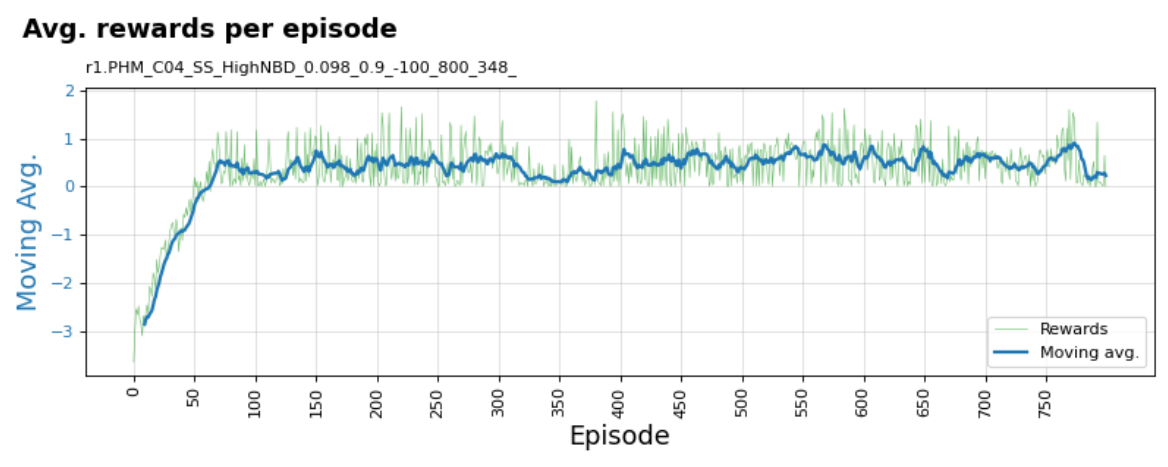


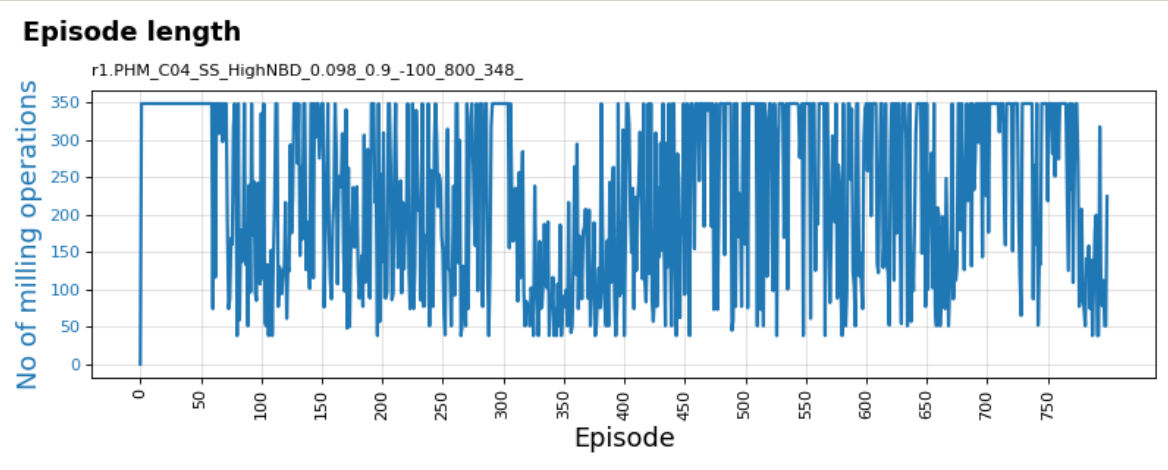


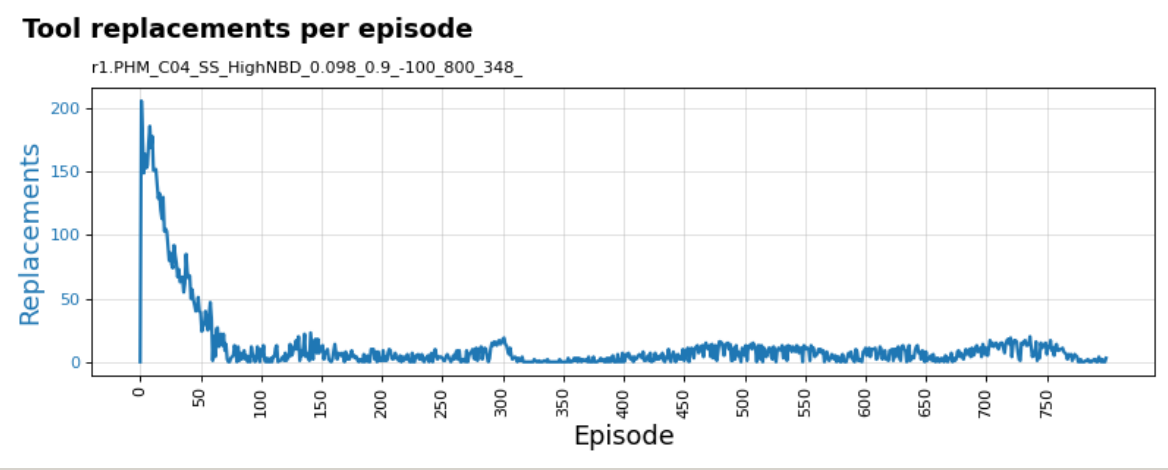
Training plots for REINFORCE algorithm

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









Discussions / Q&A

Thank you