

Experiments with REINFORCE algorithm

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Planned schedule and status: 12-Jul-2023

	Jan-23 Apr-23	May-23 Aug-23	Sep-23 Dec-23	Jan-24 Apr-24	May-24 Aug-24	Sep-24 Dec-24	Jan-25 Apr-25	May-25 Aug-25	Sep-25 Dec-25	Jan-26 Apr-26	May-26 Aug-26	Sep-26 Dec-26
Literature Research	✓											
Research on suitable public data sets	✓											
Research on suitable RL algorithms to use for PdM		✓										
Build PdM environment		✓										
Design RL elements (state, action and reward signal)		WIP										
Develop an experimental set up												
Evaluate on public data set												
Iterative phase: Experiment / fine-tune hyper-parameters												
Development of final model												
Stretch objective: Evaluate on primary data												
Modify model for adapting to primary data												
Thesis writing and submission												







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 
6. Status of Planned Objectives and Schedule 

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

$$VB = a \cdot t^{b_1} \cdot e^{b_2 \cdot t} \quad \left| \begin{array}{l} t=t_k \\ t=0 \end{array} \right.$$

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THE ANNALS OF UNIVERSITY "DUNĂREA DE JOS" OF GALAȚI
FASCICLE VIII, 2006 (XII), ISSN 1221-4590
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 analyzed 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 able 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].

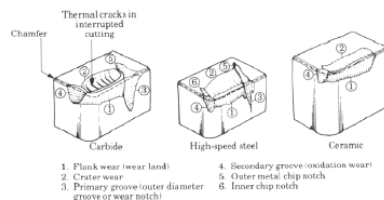


Fig. 1. Tools wear mechanisms for different tool materials [25].

◀ **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

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Datasets

Standard Dataset

2010 PHM SOCIETY CONFERENCE DATA CHALLENGE



Citation: Xinghui Li
Author(s):
Submitted by: Yi-Chung Chen
Last updated: Thu, 10/07/2021 - 06:12
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Links: 2010 PHM Society Conference Data Challenge
Fuzzy neural network modelling for tool wear estimation in dry milling operation

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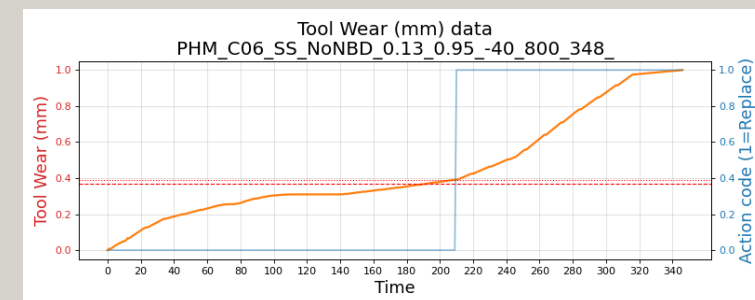
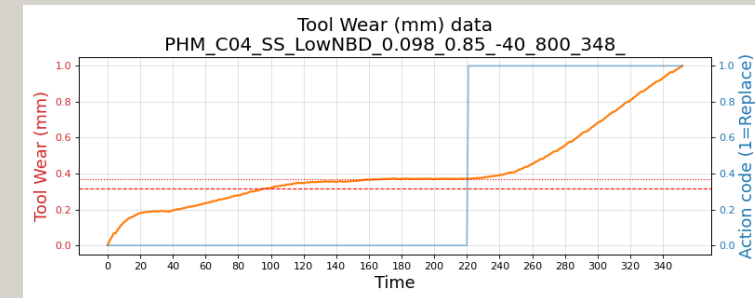
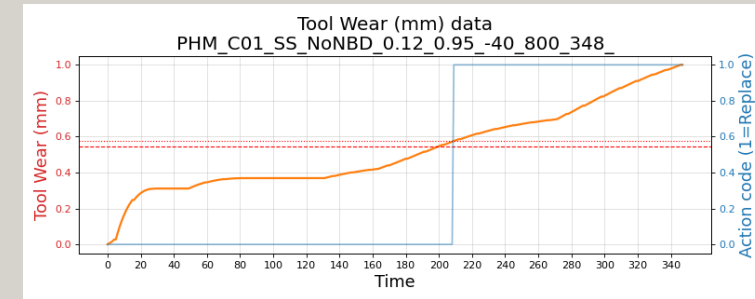
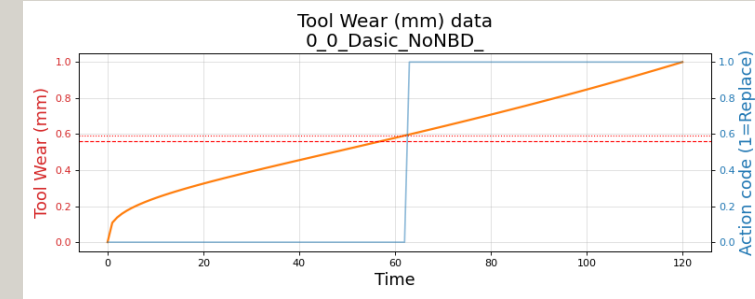
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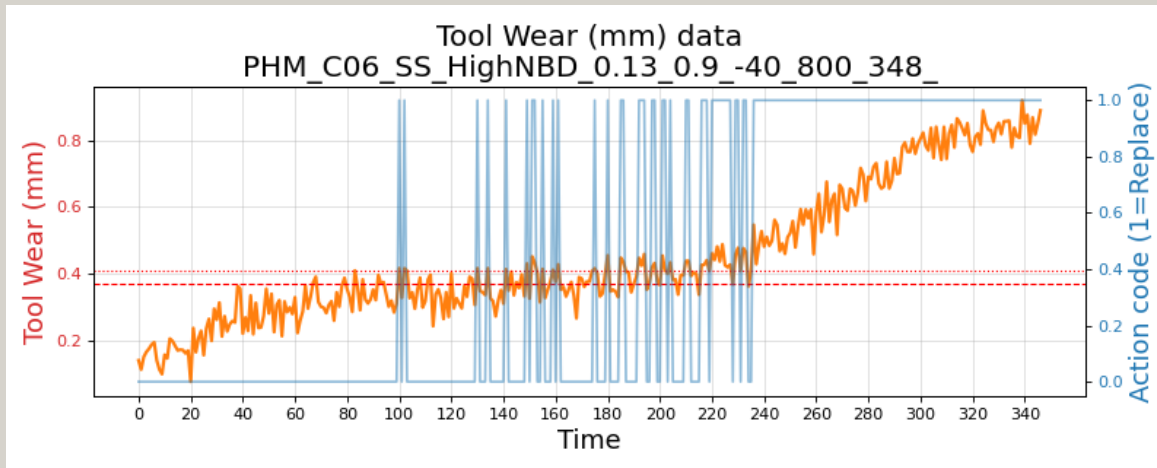
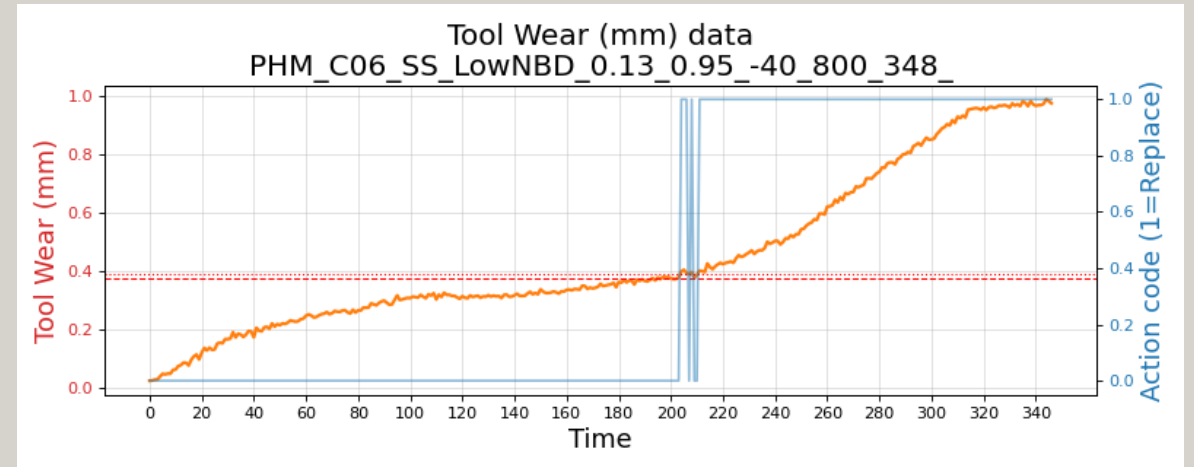
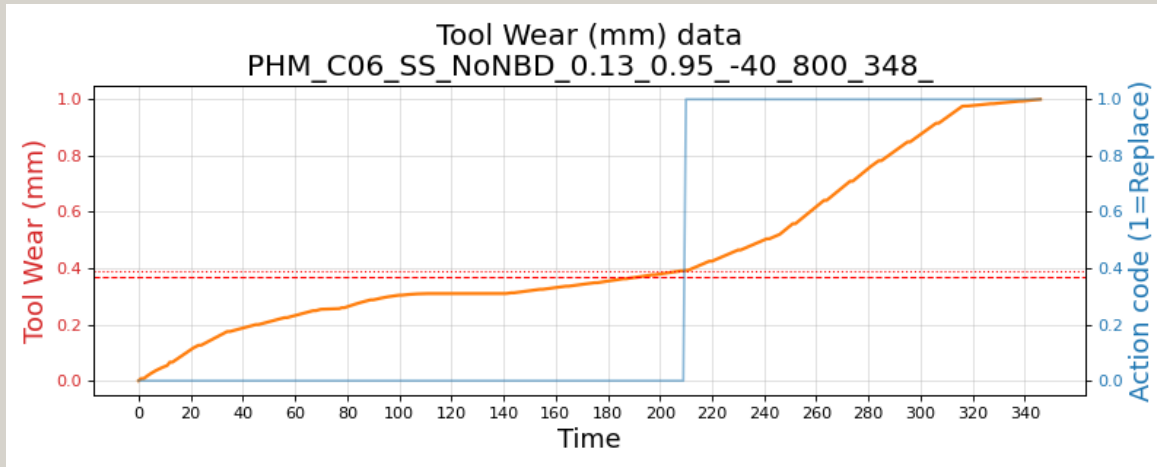
RL environment - Variants

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

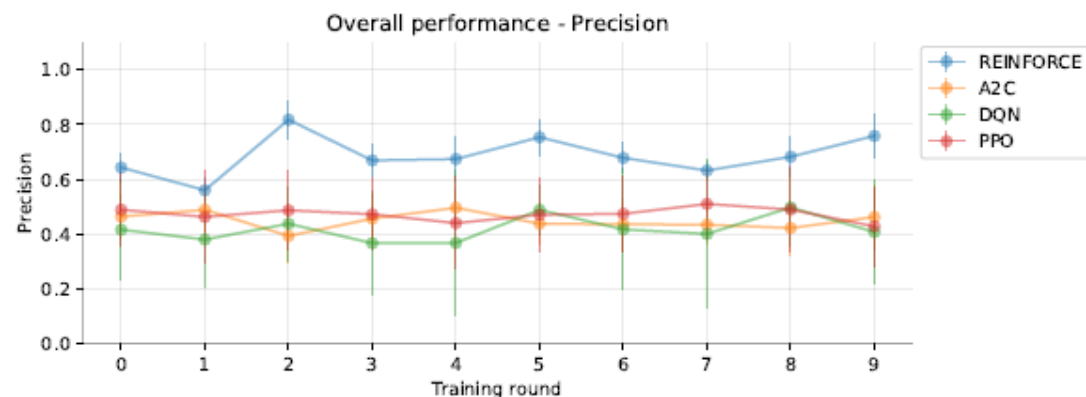
Results: Complex, multi-variate environment

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

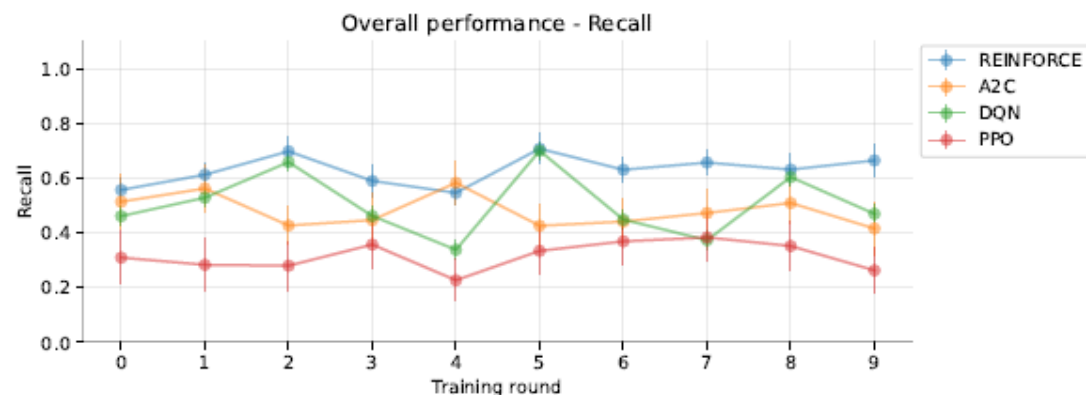
No noise or break-down

	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

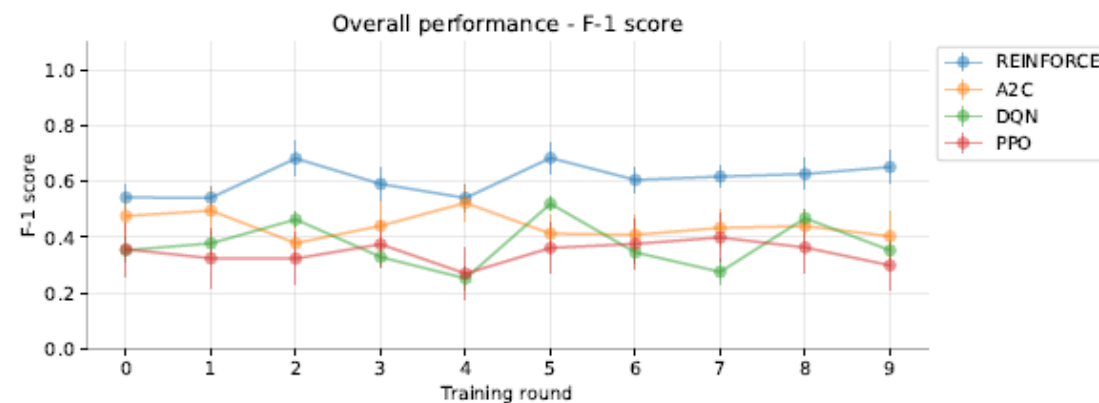
Results: Overall – Training across 10 rounds



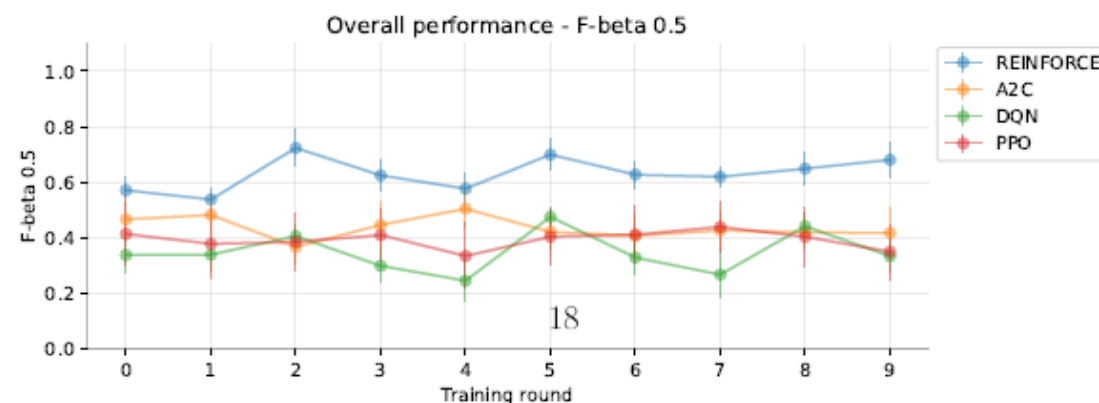
(a) Precision



(b) Recall

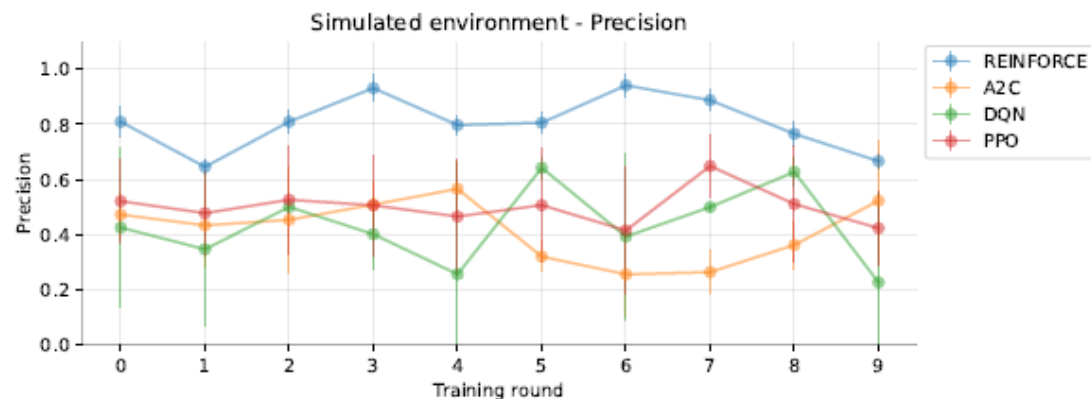


(c) F1-score

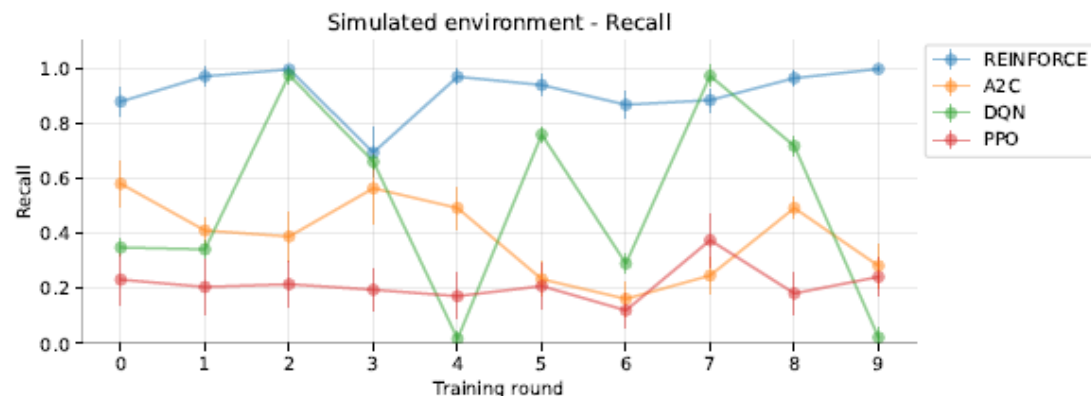


(d) F1-beta (0.5)

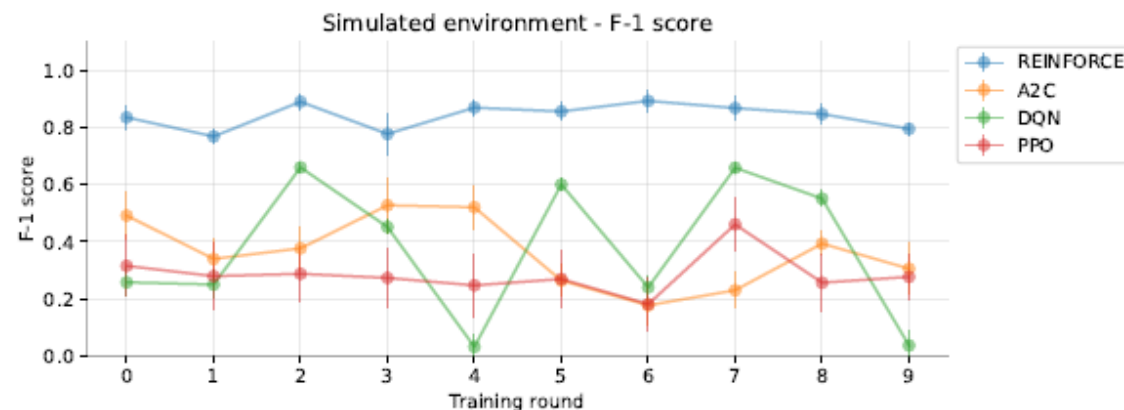
Results: Simulated – Training across 10 rounds



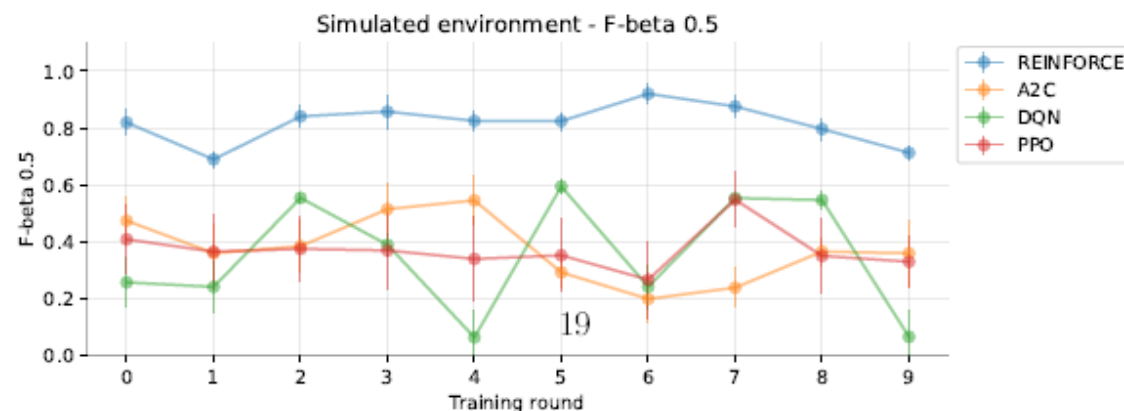
(a) Precision



(b) Recall

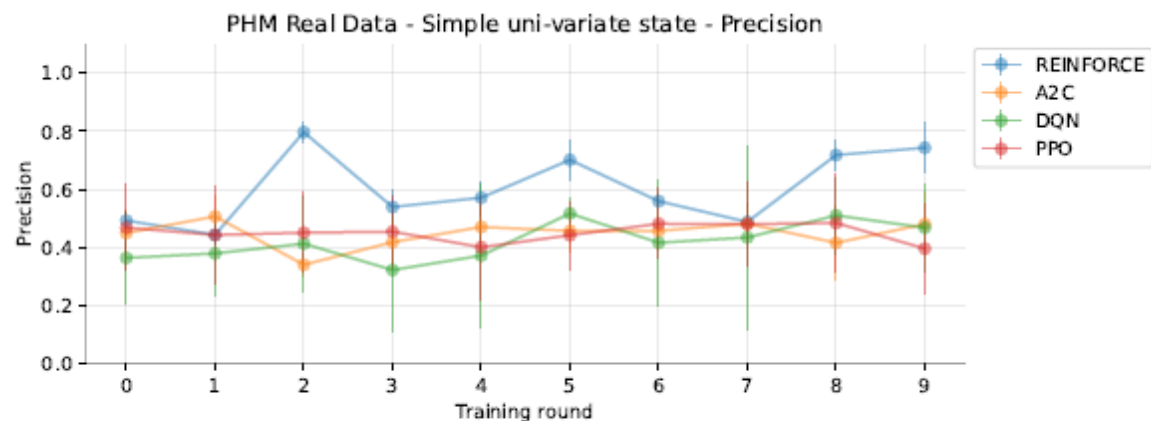


(c) F1-score

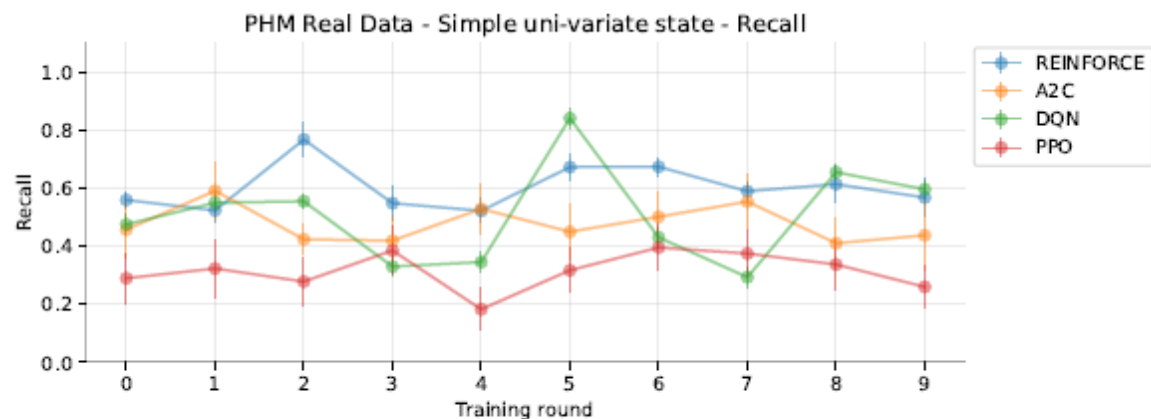


(d) F1-beta (0.5)

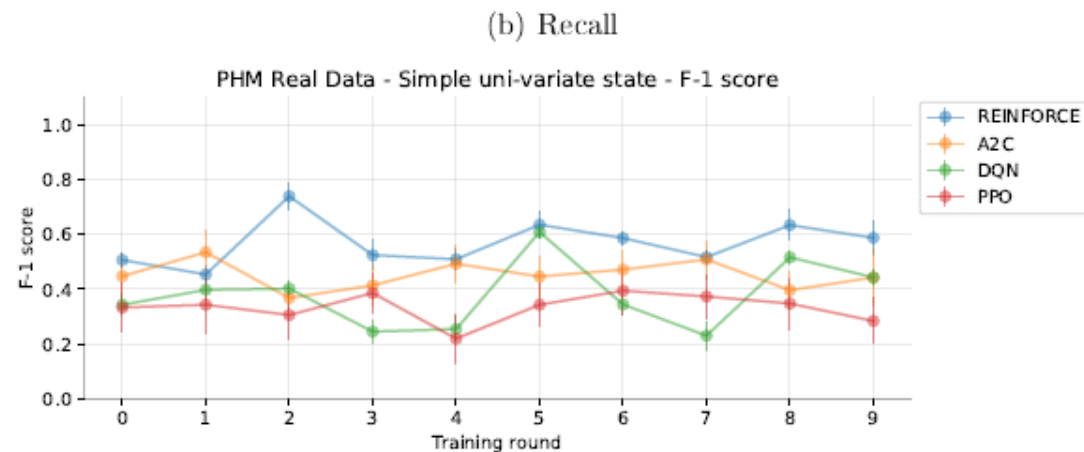
Results: PHM Real Data – 3 data-sets - Simple univariate



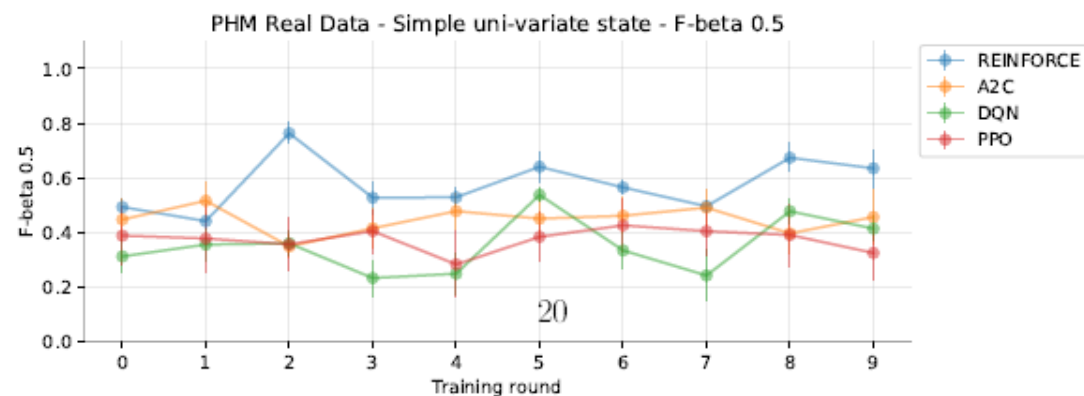
(a) Precision



(b) Recall

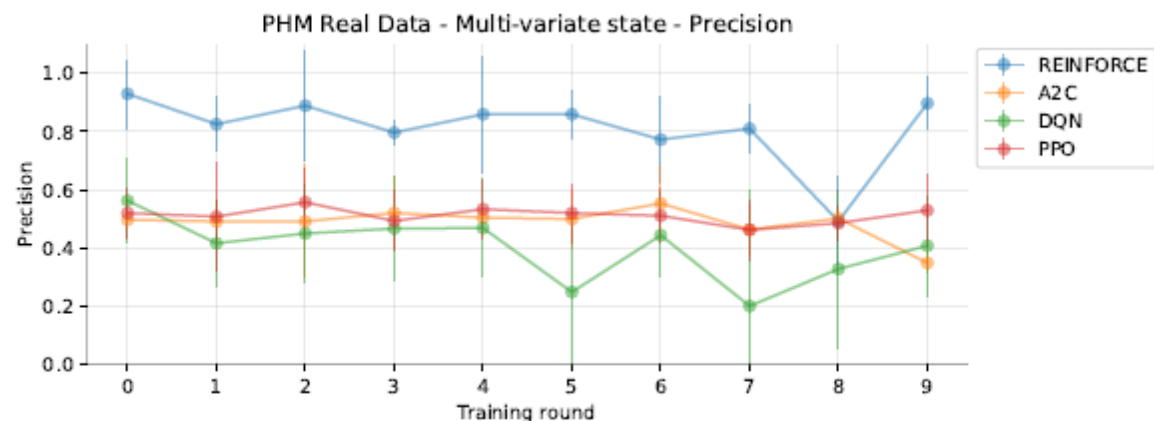


(c) F1-score

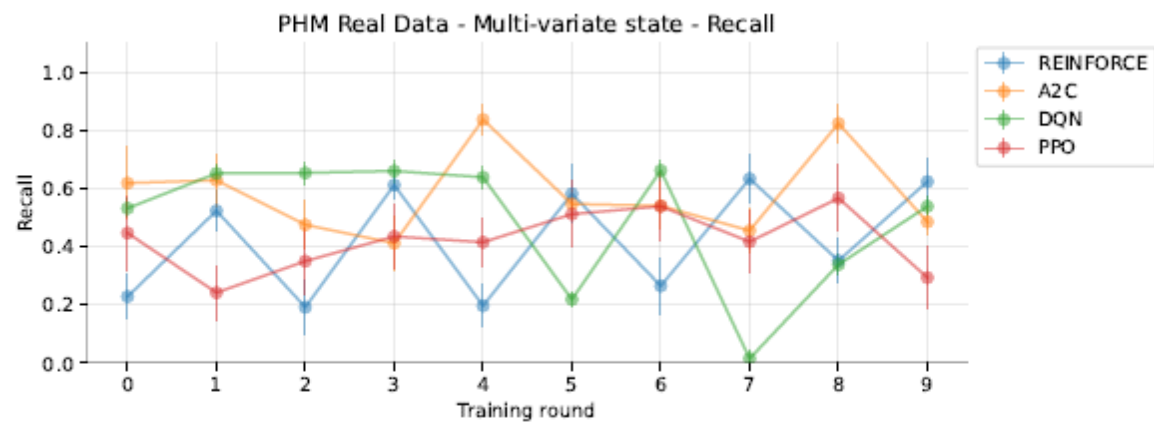


(d) F1-beta (0.5)

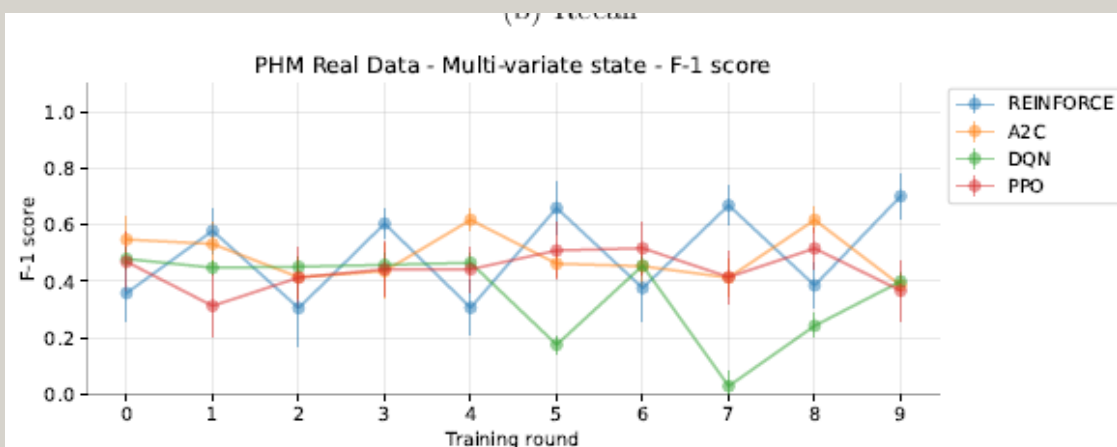
Results: PHM Real Data – 3 data-sets – Multi-variate



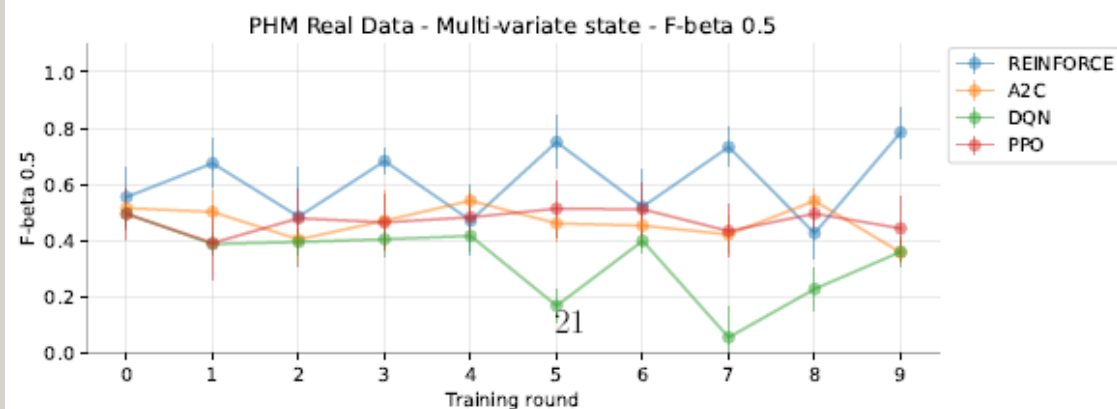
(a) Precision



(b) Recall



(c) F1-score



(d) F1-beta (0.5)

Statistical validation: Two sample, one-tail test

Two sample, one-tail test

$\alpha = 0.05$, 95% confidence

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

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				
Precision	1500	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				
Precision	300	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				
Precision	900	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				
Precision	300	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

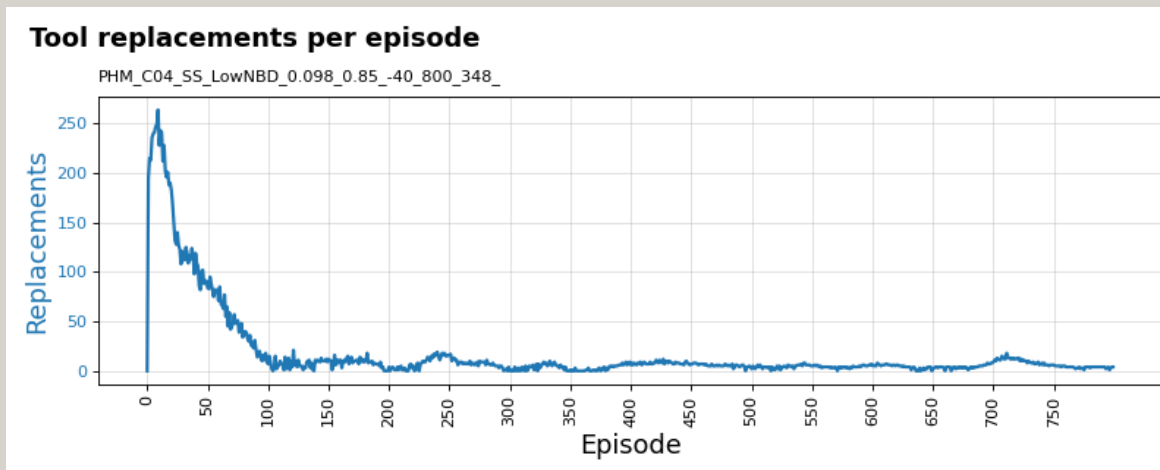
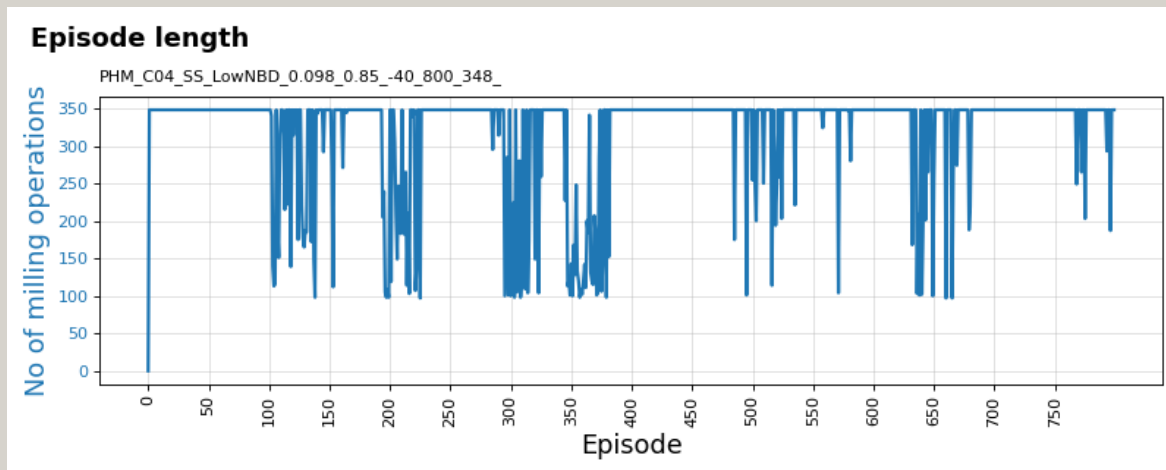
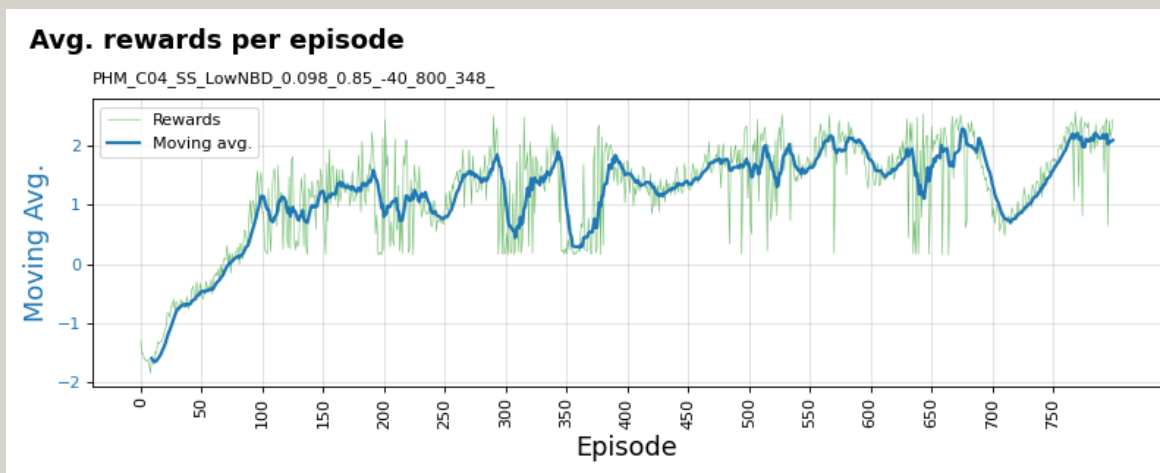
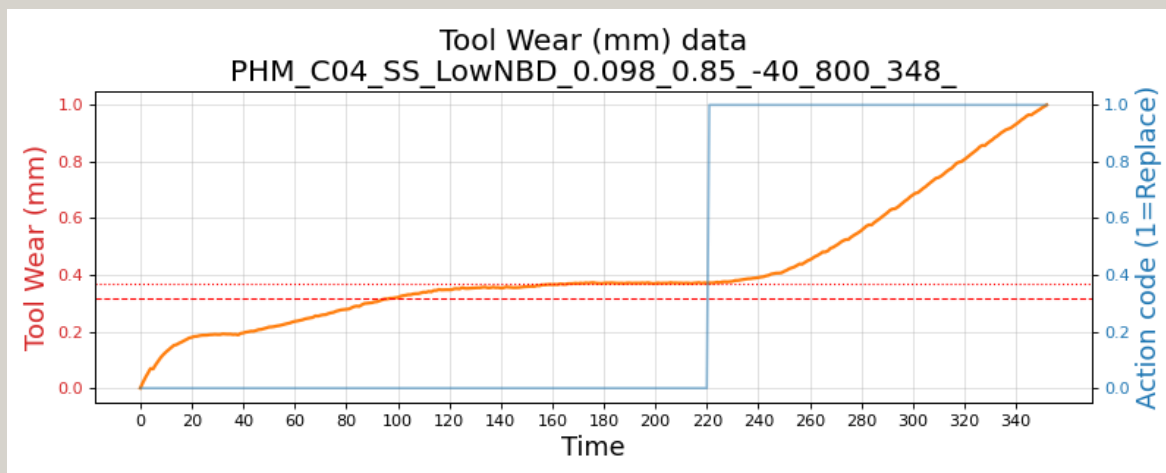
t statistic

	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

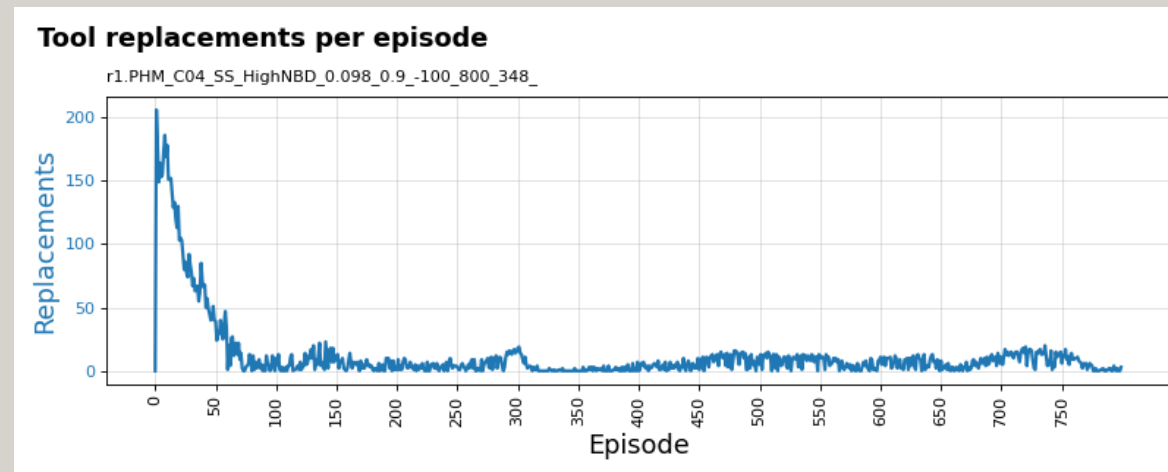
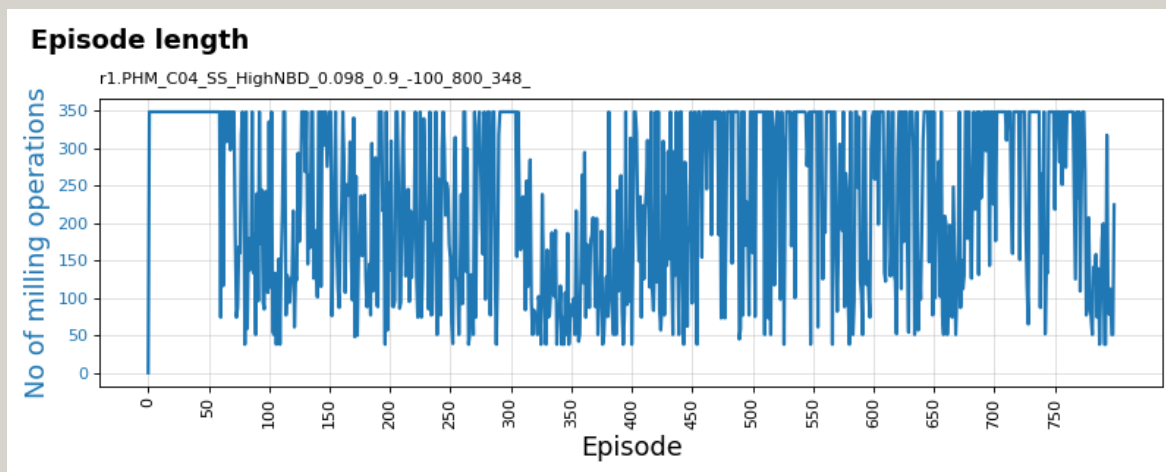
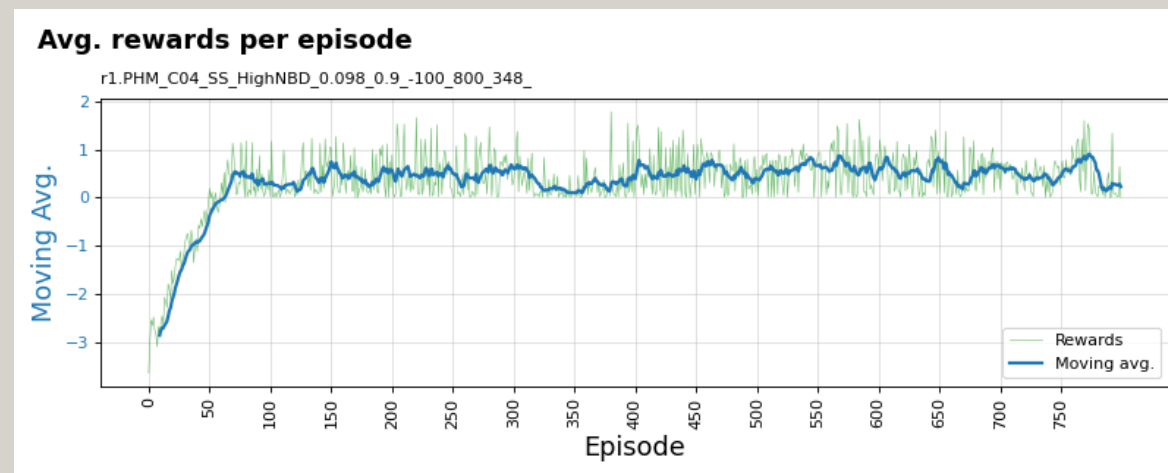
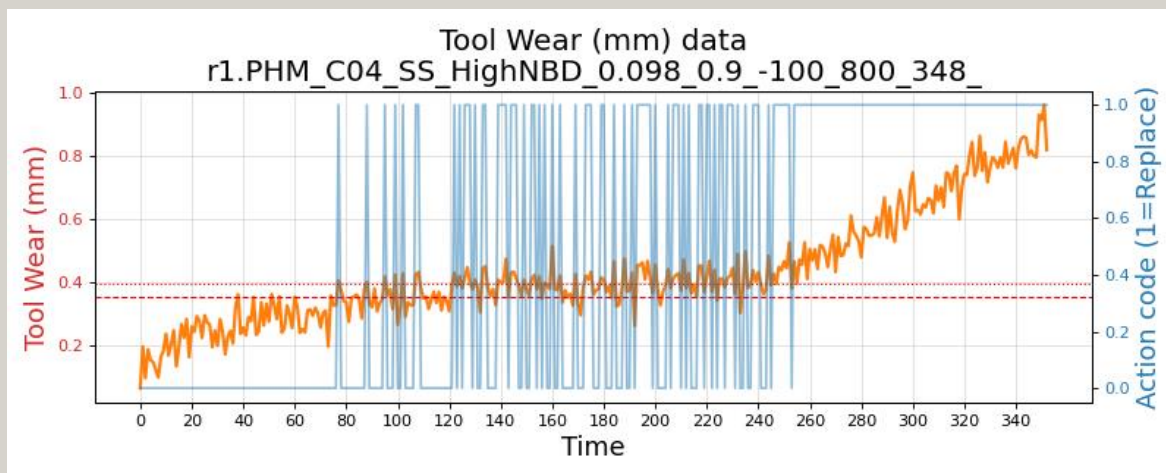
Training plots for REINFORCE algorithm

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%)



Status of Planned Objectives and Schedule

Thank you