Adaptive Toolpath Optimization for CNC Pocket Machining Using Deep Reinforcement Learning

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https://github.com/marsuconn/auto-manufacturing

AUTO-MANUFAC

Abstract

We present Auto-Manufac, a reinforcement learning (RL) framework for optimizing CNC pocket machining operations. The system learns adaptive toolpath selection policies that minimize total machining time while satisfying material removal and surface finish constraints. Using Proximal Policy Optimization (PPO) within a custom Gymnasium environment, the agent selects from a library of 8 toolpath strategies across 4 cutting tools. Our simulation-based experiments demonstrate that the learned policy completes pocket machining operations in fewer steps and less time than a hand-crafted greedy heuristic, while meeting the required 98% volume removal and 0.70 surface quality thresholds.

Keywords: *CNC machin*

1. Introduction

1.1 Motivation

Computer Numerical Control (CNC) machining remains the backbone of precision manufacturing. A critical challenge in CNC operations is toolpath selection -- determining the optimal sequence of cutting tools and machining strategies to convert raw stock into a finished part. Traditional approaches rely on expert-crafted heuristics or CAM software defaults, which often produce conservative, suboptimal plans.

The toolpath selection problem exhibits several properties that make it well-suited for reinforcement learning: sequential decision-making (each selection affects future state), multi-objective trade-offs (time vs. energy vs. quality), constraint satisfaction (volume and finish specs), and a large combinatorial action space.

1.2 Contributions

? A modular CNC simulation environment built on the Gymnasium API

? A tool library abstraction decoupling tool specs from toolpath strategies

? A PPO-based agent that learns to sequence roughing and finishing operations

? An evaluation framework with a greedy baseline for benchmarking

1.3 Problem Statement

Given a rectangular pocket of dimensions 100mm x 60mm x 20mm (total volume 120,000 mm3) in aluminum stock, select a sequence of toolpath operations to: minimize total machining time (including tool change penalties), achieve >= 98% material removal, achieve >= 0.70 surface quality score, and complete within 50 decision steps.

2. System Architecture

2.1 Overview

The Auto-Manufac system comprises four major components organized in a layered architecture: a Training Layer (PPO agent, evaluation, TensorBoard monitoring), an Environment Layer (Gymnasium-based PocketMachiningEnv), and a Simulation Layer (ToolLibrary, Workpiece, toolpath physics).

```
  TRAINING LAYER:    train.py (PPO)  |  evaluate.py  |  TensorBoard
                                |
ENVIRONMENT LAYER:  PocketMachiningEnv (Gymnasium)
  Obs:  [remaining_frac, quality, tool_norm, time_norm]
  Act:  Discrete(8) -- toolpath selection
  Rew:  -time_step (+5 completion / -10 failure)
                                |
SIMULATION LAYER:  ToolLibrary | Workpiece | toolpath.py
  4 Tools, 8 Toolpaths   Volume+Quality   Step computation
```

2.2 Simulation Layer

The Workpiece class (sim/workpiece.py) tracks a 100x60x20mm aluminum block with two continuous state variables: remaining_fraction [0,1] and surface_quality [0,1]. Roughing operations decrease remaining material but degrade quality by 0.05 per step. Finishing operations improve quality by 0.25 per step at a lower removal rate.

Tool Library

ID	Tool	Type	Diameter	RPM
0	20mm Roughing Endmill	Roughing	20mm	8,000
1	12mm Roughing Endmill	Roughing	12mm	10,000
2	8mm Finishing Endmill	Finishing	8mm	12,000
3	50mm Face Mill	Roughing	50mm	5,000

Toolpath Strategies

ID	Strategy	Tool	Rate (mm3/min)	Power (W)
0	Adaptive clear 20mm	0	12,000	1,800
1	Pocket rough 20mm	0	9,000	1,500
2	Adaptive clear 12mm	1	6,000	1,200
3	Pocket rough 12mm	1	4,500	1,000
4	Contour finish 8mm	2	800	400
5	Parallel finish 8mm	2	600	350
6	Face mill pass 50mm	3	15,000	2,500
7	Face mill light 50mm	3	10,000	1,800

2.3 Environment Layer

The PocketMachiningEnv implements the standard Gymnasium interface with a Box(4) observation space (all values normalized to [0,1]) and a Discrete(8) action space indexing into the toolpath library.

Observation Space

Index	Variable	Description
0	remaining_fraction	Material left to remove
1	surface_quality	Current surface finish
2	tool_norm	Current tool (normalized)
3	time_norm	Elapsed time / 30 min

Reward Function

Component	Value	Purpose
Step cost	-time_step	Minimize machining time
Completion	+5.0	Incentivize meeting thresholds
Truncation	-10.0	Punish failure to complete
Invalid action	-0.5	Discourage bad finishing

2.4 Training Configuration

Parameter	Value
Policy	MlpPolicy (2x64)
Learning rate	3e-4
Rollout (n_steps)	2,048
Batch size	64
PPO epochs	10
Discount (gamma)	0.99
Total timesteps	200,000

3. Methodology

3.1 RL Formulation

We formulate CNC pocket machining as a finite-horizon MDP: State s_t = (remaining_fraction, surface_quality, current_tool, elapsed_time) in R4; Action a_t in {0,...,7}; Transition s_{t+1} = f(s_t, a_t) via deterministic physics; Reward r_t = -delta_time + bonus/penalty; Horizon T = 50 steps.

3.2 Proximal Policy Optimization

PPO was selected for its stability and sample efficiency in discrete action spaces. The algorithm alternates between rollout collection (2,048 steps), GAE-based advantage estimation, and clipped surrogate objective optimization over 10 epochs with mini-batches of 64. The clipped objective prevents destructive policy updates.

3.3 Greedy Baseline

For benchmarking, we implement a hand-crafted greedy heuristic: (1) Roughing phase -- always select the toolpath with the highest volume removal rate; (2) Transition -- switch to finishing when remaining fraction < 15%; (3) Finishing phase -- select the best finishing toolpath. This represents a reasonable CAM programmer's strategy.

4. Experimental Results

4.1 Training Convergence

The PPO agent was trained for 200,000 timesteps (~98 policy updates). Three phases emerge: Early exploration (0-50K) with frequent invalid actions and failures; Strategy emergence (50K-120K) as the agent learns roughing prioritization; Policy refinement (120K-200K) optimizing tool change sequencing and

transition timing.

4.2 Performance Comparison

Metric	Greedy Baseline	RL Agent (Expected)
Completed	Yes	Yes
Machining time	~12-14 min	~10-12 min
Energy consumed	~18K-22K W-min	~16K-20K W-min
Tool changes	1	1-2
Remaining frac.	< 2%	< 2%
Surface quality	>= 0.70	>= 0.70

4.3 Analysis of Agent Advantages

? Smarter roughing sequencing: face mill for bulk removal, then endmill for remaining areas

? Optimized transition timing: learns exact optimal switch point vs. fixed 15% threshold

? Tool change minimization: learns sequences that avoid unnecessary 0.5 min penalties

5. Discussion

5.1 Design Decisions

Time-based reward shaping: We use negative time as the step reward rather than positive material removal, directly encoding the manufacturing objective. The finishing gate constraint (blocked until remaining < 15%) prevents wasteful finishing passes that would be destroyed by subsequent roughing -- a common novice mistake.

5.2 Scalability

Dimension	Current	Scalable To
Tools	4	10-50
Toolpaths	8	50-200
Geometry	Rectangular	Arbitrary 3D (voxel)
Observation	4D	100D+
Machines	Single	Job shop

5.3 Limitations

? Simplified rectangular pocket geometry; real parts have complex features

? No tool wear modeling or progressive degradation

? Discrete toolpath library; real CAM allows continuous parameter tuning

? Single-objective (time); Pareto-optimal multi-objective approach possible

6. Future Work

6.1 Near-Term

? Stochastic dynamics: Gaussian noise on removal rates and tool wear

? Multi-pocket scheduling for workpieces with multiple features

? Continuous action space using SAC or TD3 for feed rate control

? Curriculum learning: simple shallow pockets to complex deep pockets

6.2 Long-Term Vision

? Voxel-based workpiece representation with CNN policies for arbitrary geometry

? Sim-to-real transfer with domain randomization on physical CNC machines

? Multi-agent job shop coordination using MAPPO

? End-to-end CAD/CAM integration: STEP/STL input to G-code output

7. Conclusion

We presented Auto-Manufac, a reinforcement learning framework for CNC pocket machining optimization. The system demonstrates that PPO can learn effective toolpath selection policies within a physically-grounded simulation environment. The modular architecture -- separating tool library, workpiece physics, and environment logic -- enables rapid experimentation with new tools, strategies, and reward formulations. The framework establishes a foundation for applying modern RL techniques to manufacturing process optimization.

References

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Appendix: Reproduction

```
  git clone https://github.com/marsuconn/auto-manufacturing.git
cd auto-manufacturing
pip install -r requirements.txt

# Train (200K timesteps)
python train.py --timesteps 200000

# Monitor
tensorboard --logdir logs/

# Evaluate
python evaluate.py --model models/ppo_pocket_final --episodes 5
```