BLENDING MPC & VALUE FUNCTION APPROXIMATION FOR EFFICIENT REINFORCEMENT LEARNING

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ABSTRACT

Model-Predictive Control (MPC) is a powerful tool for controlling complex, real-world systems that uses a model to make predictions about future behavior. For each state encountered, MPC solves an online optimization problem to choose a control action that will minimize future cost. This is a surprisingly effective strategy, but real-time performance requirements warrant the use of simple models. If the model is not sufficiently accurate, then the resulting controller can be biased, limiting performance. We present a framework for improving on MPC with model-free reinforcement learning (RL). The key insight is to view MPC as constructing a series of local Q-function approximations. We show that by using a parameter λ, similar to the trace decay parameter in TD(λ), we can systematically trade-off learned value estimates against the local Q-function approximations. We present a theoretical analysis that shows how error from inaccurate models in MPC and value function estimation in RL can be balanced. We further propose an algorithm that changes λ over time to reduce the dependence on MPC as our estimates of the value function improve, and test the efficacy our approach on challenging high-dimensional manipulation tasks with biased models in simulation. We demonstrate that our approach can obtain performance comparable with MPC with access to true dynamics even under severe model bias and is more sample efficient as compared to model-free RL.

1 INTRODUCTION

Model-free Reinforcement Learning (RL) is increasingly used in challenging sequential decision-making problems including high-dimensional robotics control tasks (Haarnoja et al., 2018; Schulman et al., 2017) as well as video and board games (Silver et al., 2016; 2017). While these approaches are extremely general, and can theoretically solve complex problems with little prior knowledge, they also typically require a large quantity of training data to succeed. In robotics and engineering domains, data may be collected from real-world interaction, a process that can be dangerous, time consuming, and expensive.

Model-Predictive Control (MPC) offers a simpler, more practical alternative. While RL typically uses data to learn a global model offline, which is then deployed at test time, MPC solves for a policy *online* by optimizing an approximate model for a finite horizon at a given state. This policy is then executed for a single timestep and the process repeats. MPC is one of the most popular approaches for control of complex, safety-critical systems such as autonomous helicopters (Abbeel et al., 2010), aggressive off-road vehicles (Williams et al., 2016) and humanoid robots (Erez et al., 2013), owing to its ability to use approximate models to optimize complex cost functions with nonlinear constraints.

However, approximations in the model used by MPC can significantly limit performance. Specifically, *model bias* may result in *persistent errors* that eventually compound and become catastrophic. For example, in non-prehensile manipulation, practitioners often use a simple quasi-static model that assumes an object does not roll or slide away when pushed. For more dynamic objects, this can lead to aggressive pushing policies that perpetually over-correct, eventually driving the object off the surface.

Recently, there have been several attempts to combine MPC with model free RL, showing that the combination can improve over the individual approaches alone. Many of these approaches involve using RL to learn a terminal cost function, thereby increasing the effective horizon of MPC (Zhong et al., 2013; Lowrey et al., 2018; Bhardwaj et al., 2020). However, the learned value function is only applied at the end of the MPC horizon. Model errors would still persist in horizon, leading to sub-optimal policies. Similar approaches have also been applied to great effect in discrete games with known models (Silver et al., 2016;

2017; Anthony et al., 2017), where value functions and policies learned via model-free RL are used to guide Monte-Carlo Tree Search. In this paper, we focus on a somewhat broader question: can machine learning be used to both increase the effective horizon of MPC, while also correcting for model bias?

One straightforward approach is to try to learn (or correct) the MPC model from real data encountered during execution; however there are some practical barriers to this strategy. Hand-constructed models are often crude-approximations of reality and lack the expressivity to represent encountered dynamics. Moreover, increasing the complexity of such models leads to computationally expensive updates that can harm MPC's online performance. Model-based RL approaches such as Chua et al. (2018); Nagabandi et al. (2018); Shyam et al. (2019) aim to learn general neural network models directly from data. However, learning globally consistent models is an exceptionally hard task due to issues such as covariate shift (Ross & Bagnell, 2012).

We propose a framework, MPQ(λ), for weaving together MPC with learned value estimates to trade-off errors in the MPC model and approximation error in a learned value function. Our key insight is to view MPC as tracing out a series of local Q-function approximations. We can then blend each of these Q-functions with value estimates from reinforcement learning. We show that by using a blending parameter λ, similar to the trace decay parameter in TD(λ), we can systematically trade-off errors between these two sources. Moreover, by smoothly decaying λ over learning episodes we can achieve the best of both worlds - a policy can depend on a prior model before its has encountered any data and then gradually become more reliant on learned value estimates as it gains experience.

To summarize, our key contributions are:
1. A framework that unifies MPC and Model-free RL through value function approximation.
2. Theoretical analysis of finite horizon planning with approximate models and value functions.
3. Empirical evaluation on challenging manipulation problems with varying degrees of model-bias.

2 Preliminaries

2.1 Reinforcement Learning

We consider an agent acting in an infinite-horizon discounted Markov Decision Process (MDP). An MDP is defined by a tuple $\mathcal{M} = (\mathcal{S},\mathcal{A},c,P,\gamma,\mu)$ where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, $c(s,a)$ is the per-step cost function, $s_{t+1} \sim P(\cdot|s_t,a_t)$ is the stochastic transition dynamics and γ is the discount factor and $\mu(s_0)$ is a distribution over initial states. A closed-loop policy $\pi(\cdot|s)$ outputs a distribution over actions given a state. Let $\mu^{\pi}_{\mathcal{M}}$ be the distribution over state-action trajectories obtained by running policy π on $\mathcal{M}$. The value function for a given policy π, is defined as $V^{\pi}_{\mathcal{M}}(s) = \mathbb{E}_{\mu^{\pi}_{\mathcal{M}}}[\sum_{t=0}^{\infty}\gamma^t c(s_t,a_t) \,|\, s_0 = s]$ and the action-value function as $Q^{\pi}_{\mathcal{M}}(s,a) = \mathbb{E}_{\mu^{\pi}_{\mathcal{M}}}[\sum_{t=0}^{\infty}\gamma^t c(s_t,a_t) \,|\, s_0 = s, a_0 = a]$. The objective is to find an optimal policy $\pi^* = \underset{\pi}{\operatorname{argmin}}\, \mathbb{E}_{s_0\sim\mu}[V^{\pi}_{\mathcal{M}}(s_0)]$. We can also define the (dis)-advantage function $A^{\pi}_{\mathcal{M}}(s,a) = Q^{\pi}_{\mathcal{M}}(s,a) - V^{\pi}(s)$, which measures how good an action is compared to the action taken by the policy in expectation. It can be equivalently expressed in terms of the Bellman error as $A^{\pi}_{\mathcal{M}}(s,a) = c(s,a) + \gamma\mathbb{E}_{s'\sim P, a'\sim\pi}[Q^{\pi}_{\mathcal{M}}(s',a')] - \mathbb{E}_{a\sim\pi}[Q^{\pi}_{\mathcal{M}}(s,a)]$.

2.2 Model-Predictive Control

MPC is a widely used technique for synthesizing closed-loop policies for MDPs. Instead of trying to solve for a single, globally optimal policy, MPC follows a more pragmatic approach of optimizing simple, local policies *online*. At every timestep on the system, MPC uses an approximate model of the environment to search for a parameterized policy that minimizes cost over a finite horizon. An action is sampled from the policy and executed on the system. The process is then repeated from the next state, often by warm-starting the optimization from the previous solution.

We formalize this process as solving a simpler *surrogate* MDP $\hat{\mathcal{M}} = (\mathcal{S},\mathcal{A},\hat{c},\hat{P},\gamma,\hat{\mu},H)$ online, which differs from $\mathcal{M}$ by using an approximate cost function $\hat{c}$, transition dynamics $\hat{P}$ and limiting horizon to H. Since it plans to a finite horizon, it's also common to use a terminal state-action value function $\hat{Q}$ that estimates the cost-to-go. The start state distribution $\hat{\mu}$ is a dirac-delta function centered on the current state $s_0 = s_t$. MPC can be viewed as iteratively constructing an estimate of the Q-function of the original MDP $\mathcal{M}$, given policy π_ϕ at state s:

$$Q^{\phi}_{H}(s,a) = \mathbb{E}_{\mu^{\pi_\phi}_{\hat{\mathcal{M}}}}\left[\sum_{i=0}^{H-1}\gamma^i\hat{c}(s_i,a_i) + \gamma^H\hat{Q}(s_H,a_H) \,|\, s_0 = s, a_0 = a\right] \tag{1}$$

MPC then iteratively optimizes this estimate (at current system state s_t) to update the policy parameters

$$\phi_t^* = \underset{\phi}{\operatorname{argmin}}\, Q_H^{\phi}(s_t, \pi_\phi(s_t)) \tag{2}$$

Alternatively, we can also view the above procedure from the perspective of disadvantage minimization. Let us define an estimator for the 1-step disadvantage with respect to the potential function $\hat{Q}$ as $A(s_i,a_i) = c(s_i,a_i) + \gamma \hat{Q}(s_{i+1},a_{i+1}) - \hat{Q}(s_i,a_i)$. We can then equivalently write the above optimization as minimizing the discounted sum of disadvantages over time via the telescoping sum trick

$$\underset{\pi \in \Pi}{\operatorname{argmin}}\, \mathbb{E}_{\mu_{\mathcal{M}}^{\pi_\phi}} \left[\hat{Q}(s_0,a_0) + \lambda \sum_{i=0}^{H-1} \gamma^i A(s_i,a_i) \,|\, s_0 = s_t \right] \tag{3}$$

Although the above formulation queries the $\hat{Q}$ at every timestep, it is still exactly equivalent to the original problem and hence, does not mitigate the effects of model-bias. In the next section, we build a concrete method to address this issue by formulating a novel way to blend Q-estimates from MPC and a learned value function that can balance their respective errors.

3 Mitigating Bias in MPC via Reinforcement Learning

In this section, we develop our approach to systematically deal with model bias in MPC by blending-in learned value estimates. First we take a closer look at the different sources of error in the estimate in (1) and then propose an easy-to-implement, yet effective strategy for trading them off.

3.1 Sources of Error in MPC

The performance of MPC algorithms critically depends on the quality of the Q-function estimator $Q_H^{\phi}(s,a)$ in (1). There are three major sources of approximation error. First, model bias can cause compounding errors in predicted state trajectories, which biases the estimates of the costs of different action sequences. The effect of model error becomes more severe as $H \to \infty$. Second, the error in the terminal value function gets propagated back to the estimate of the Q-function at the start state. With discounting, the effect of error due to inaccurate terminal value function diminishes as H increases. Third, using a small H with an inaccurate terminal value function can make the MPC algorithm greedy and myopic to rewards further out in the future.

We can formally bound the performance of the policy with approximate models and approximate learned value functions. In Theorem 3.1, we show the loss in performance of the resulting policy as a function of the model error, value function error and the planning horizon. Further, in Theorem 3.2 we provide the optimal horizon H^* that minimizes performance loss when errors are known.

Theorem 3.1 (Proof Appendix A.1.2)**.** *Let MDP $\hat{\mathcal{M}}$ be an α-approximation of $\mathcal{M}$ such that $\forall(s,a)$, we have $\left|\left|\hat{P}(s'|s,a) - P(s'|s,a)\right|\right|_1 \leq \alpha$ and $|\hat{c}(s,a) - c(s,a)| \leq \alpha$. Let the learned value function $\hat{Q}(s,a)$ be an ϵ-approximation of the true value function $\left|\left|\hat{Q}(s,a) - Q_{\mathcal{M}}^{\pi^*}(s,a)\right|\right|_\infty \leq \epsilon$. The performance of the MPC policy is bounded w.r.t the optimal policy as $\left|\left|V_{\mathcal{M}}^{\pi^*}(s) - V_{\hat{\mathcal{M}}}^{\hat{\pi}}(s)\right|\right|_\infty$*

$$\leq 2\left(\frac{\gamma(1-\gamma^{H-1})}{(1-\gamma^H)(1-\gamma)} \alpha H \left(\frac{c_{\max} - c_{\min}}{2} \right) + \frac{\gamma^H \alpha H}{1-\gamma^H} \left(\frac{V_{\max} - V_{\min}}{2} \right) + \frac{\alpha}{1-\gamma} + \frac{\gamma^H \epsilon}{1-\gamma^H} \right) \tag{4}$$

This theorem generalizes over various established results. Setting $H = 1, \epsilon = 0$ gives us the 1-step simulation lemma in Kearns & Singh (2002) (Appendix A.1.1). Setting $\alpha = 0$, i.e. true model, recovers the cost-shaping result in Sun et al. (2018).

Further inspecting terms in (4), we see that the model error *increases* with horizon H (the first two terms) while the learned value error *decreases* with H. This matches our intuitions and indicates that there is an optimal planning horizon H^* that minimizes the bound.

Theorem 3.2. *The optimal planning horizon that minimizes the bound in (4) is given by*

$$H^* = \max\left(1.0, \min\left(H, \frac{\epsilon}{(1-\gamma)(\epsilon + \alpha \frac{V_{\max} - V_{\min}}{4})} \right) \right) \tag{5}$$

In practice, the errors in model and value function are usually unknown and hard to estimate making it impossible to set the MPC horizon to the optimal value. Instead, we next propose a strategy to blend the Q-estimates from MPC and the learned value function at every timestep along the horizon, instead of just the terminal step such that we can properly balance the different sources of error.

3.2 Blending Model Predictive Control and Value Functions

A naive way to blend Q-estimates from MPC with Q-estimates from the value function would be to consider a convex combination of the two

$$(1-\lambda)\underbrace{\hat{Q}(s,a)}_{\text{model-free}}+\lambda\underbrace{Q_H^{\phi}(s,a)}_{\text{model-based}} \tag{6}$$

where $\lambda \in [0,1]$. Here, the value function is contributing to a residual that is added to the MPC output, an approach commonly used to combine model-based and model-free methods (Lee et al., 2020). However, this is solution is rather *ad hoc*. If we have at our disposal a value function, why invoke it at only at the first and last timestep? As the value function gets better, it should be useful to invoke it *at all timesteps*.

Instead, consider the following recursive formulation for the Q-estimate. Given (s_i,a_i), the state-action encountered at horizon i, the blended estimate $Q^{\lambda}(s_i,a_i)$ is expressed as

$$\underbrace{Q^{\lambda}(s_i,a_i)}_{\text{current blended estimate}} = (1-\lambda)\underbrace{\hat{Q}(s_i,a_i)}_{\text{model-free}}+\lambda(\underbrace{\hat{c}(s_i,a_i)}_{\text{model-based}}+\gamma\underbrace{Q^{\lambda}(s_{i+1},a_{i+1})}_{\text{future blended estimate}}) \tag{7}$$

where $\lambda \in [0,1]$. The recursion ends at $Q^{\lambda}(s_H,a_H)=\hat{Q}(s_H,a_H)$. In other words, the current blended estimate is a convex combination of the model-free value function and the one-step model-based return. The return in turn uses the future blended estimate. Note unlike (6), the model-free estimate is invoked at *every timestep*.

We can unroll (7) in time to show $Q_H^{\lambda}(s,a)$, the blended $H-$horizon estimate, is simply an exponentially weighted average of *all horizon* estimates

$$Q_H^{\lambda}(s,a)=(1-\lambda)\sum_{i=0}^{H-1}\lambda^i Q_i^{\phi}(s,a)+\lambda^H Q_H^{\phi}(s,a) \tag{8}$$

where $Q_k^{\phi}(s,a)=\mathbb{E}_{\mu_{\mathcal{M}}^{\pi_{\phi}}}\left[\sum_{i=0}^{k-1}\gamma^i\hat{c}(s_i,a_i)+\gamma^k\hat{Q}(s_k,a_k)\,|\,s_0=s,a_0=a\right]$ is a k-horizon estimate. When $\lambda=0$, the estimator reduces to the just using $\hat{Q}$ and when $\lambda=1$ we recover the original MPC estimate Q_H in (1). For intermediate values of λ, we interpolate smoothly between the two by interpolating all H estimates.

Implementing (8) naively would require running H versions of MPC and then combining their outputs. This is far too expensive. However, we can switch to the disadvantage formulation by applying a similar telescoping trick

$$Q_H^{\lambda}(s,a)=\mathbb{E}_{\mu_{\mathcal{M}}^{\pi_{\phi}}}\left[\hat{Q}(s_0,a_0)+\sum_{i=0}^{H-1}(\gamma\lambda)^i A(s_i,a_i)\right] \tag{9}$$

This estimator has a similar form as the $TD(\lambda)$ estimator for the value function. However, while $TD(\lambda)$ uses the λ parameter for bias-variance trade-off, our blended estimator aims trade-off bias in dynamics model with bias in learned value function.

Corollary 3.1 (Proof in Appendix A.1.4)**.** *For approximate models and learnt value functions as defined in Theorem. 3.1, there exist a critical $\lambda^* \in [0,1]$ that minimizes the performance bound*

$$\lambda^*=\frac{1}{\gamma}\left(1-\frac{1}{H^*}\right) \tag{10}$$

where H^* is stated in (5) in Theorem 3.2.

λ^* follows a similar trend as H^* – as learnt value error decreases, $H^* \to 1$ and $\lambda^* \to 0$.

Why use blending λ when one can simply tune horizon H? Firstly, H limits the *resolution* we can tune since it's an integer – as H gets smaller the resolution becomes worse. Secondly, the blended estimator $Q_H^{\lambda}(s,a)$ uses far more samples. Even if both Q_H^{λ} and $Q_{H^*}^{\phi}$ had the same bias, the latter uses a strict subset of samples as the former. Hence the variance of the blended estimator will be lower, with high probability.

Algorithm 1: MPQ(λ)

Input: Initial Q-function weights θ, Approximate dynamics $\hat{P}$ and cost function $\hat{c}$
Parameter: MPC horizon H, λ schedule $[\lambda_1, \lambda_2, ...]$,
discount factor γ, minibatch size K, num mini-batches N, update frequency t_{update}

$\mathcal{D} \leftarrow \emptyset$
for $t = 1 ... \infty$ **do**
  `// Update λ`
  $\lambda = \lambda_t$
  `// Blended MPC action selection`
  $\phi_t \leftarrow \underset{\phi}{\text{argmin}}\, \mathbb{E}_{\mu_{\mathcal{M}}^{\pi_\phi}} \left[\hat{Q}_\theta(s_0, a_0) + \sum_{i=0}^{H-1} (\gamma\lambda)^i A(s_i, a_i) \,|\, s_0 = s_t \right]$
  $a_t \sim \pi_{\phi_t}$
  Execute a_t on the system and observe (c_t, s_{t+1})
  $\mathcal{D} \leftarrow (s_t, a_t, c_t, s_{t+1})$
  if $t \% t_{update} == 0$ **then**
    Sample N minibatches $\left(\left\{ s_{k,n}, a_{k,n}, c_{k,n}, s'_{k,n} \right\}_{k=1}^{K} \right)_{n=1}^{N}$ from $\mathcal{D}$
    `// Generate Blended MPC value targets`
    $\hat{y}_{k,n} = c_{k,n} + \gamma \min \mathbb{E}_{\mu_{\mathcal{M}}^{\pi_\phi}} \left[\hat{Q}_\theta(s_0, a_0) + \sum_{i=0}^{H-1} (\gamma\lambda)^i A(s_i, a_i) \,|\, s_0 = s'_{k,n} \right]$
    Update θ with SGD on loss $\mathcal{L} = \frac{1}{N} \frac{1}{K} \sum_{n=1}^{N} \sum_{k=1}^{K} \left(\hat{y}_{k,n} - \hat{Q}_\theta(s_{k,n}, a_{k,n}) \right)^2$

4 THE MPQ(λ) ALGORITHM

We develop a simple variant of Q-Learning, called Model-Predictive Q-Learning with λ Weights (MPQ(λ)) that learns a parameterized Q-function estimate $\hat{Q}_\theta$. Our algorithm, presented in Alg. 1, modifies Q-learning to use blended Q-estimates as described in the (9) for both action selection and generating value targets. The parameter λ is used to trade-off the errors due to model-bias and learned Q-function, $\hat{Q}_\theta$. This can be viewed as an extension of the MPQ algorithm from Bhardwaj et al. (2020) to explicitly deal with model bias by incorporating information from the learned Q-function at all timesteps. Unlike MPQ, we do not consider the entropy-regularized formulation.

At every timestep t, MPQ(λ) proceeds by using H-horizon MPC from the current state s_t to optimize a policy π_ϕ with parameters ϕ. We modify the MPC algorithm to optimize for the greedy policy with respect to the blended Q-estimator in (9), that is

$$\phi_t^* = \underset{\phi}{\text{argmin}}\, \mathbb{E}_{\mu_{\mathcal{M}}^{\pi_\phi}} \left[\hat{Q}_\theta(s_0, a_0) + \sum_{i=0}^{H-1} (\gamma\lambda)^i A(s_i, a_i) \,|\, s_0 = s_t \right] \tag{11}$$

An action sampled from the resulting policy is then executed on the system. A commonly used heuristic is to warm start the above optimization by shifting forward the solution from the previous timestep, which serves as a good initialization if the noise in the dynamics in small (Wagener et al., 2019). This can significantly cut computational cost by reducing the number of iterations required to optimize (11) at every timestep.

Periodically, the parameters θ are updated via stochastic gradient descent to minimize the following loss function with N mini-batches of experience tuples of size K sampled from the replay buffer

$$\mathcal{L}(\theta) = \frac{1}{N} \frac{1}{K} \sum_{n=1}^{N} \sum_{k=1}^{K} \left(\hat{y}_{k,n} - \hat{Q}_\theta(s_{k,n}, a_{k,n}) \right)^2 \tag{12}$$

The H-horizon MPC with blended Q-estimator is again invoked to calculate the targets

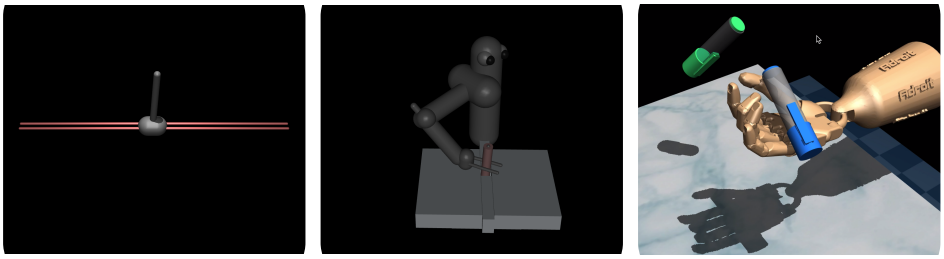


Figure 1: Tasks for evaluating MPQ(λ). Left to right - cartpole, peg insertion with 7DOF arm, and in-hand manipulation to orient align pen(blue) with target(green) with 24DOF dexterous hand.

$$\hat{y}_j = c(s_j, a_j) + \gamma \min \mathbb{E}_{\mu_{\mathcal{M}}^{\pi_\phi}} \left[\hat{Q}_\theta(s_0, a_0) + \sum_{i=0}^{H-1} (\gamma\lambda)^i A(s_i, a_i) \,|\, s_0 = s'_{k,n} \right] \tag{13}$$

Using MPC to reduce error in Q-targets has been previously explored in literature (Lowrey et al., 2018; Bhardwaj et al., 2020), where the model is either assumed to be perfect or model-error is not explicitly accounted for. MPC with the blended Q-estimator and an appropriate λ allows us to generate more stable Q-targets than using Q_θ or model-based rollouts with a terminal Q-function alone. However, running H-horizon optimization for all samples in a mini-batch can be time-consuming, forcing the use of smaller batch sizes and sparse updates. In our experiments, we employ a practical modification where during the action selection step, MPC is also queried for value targets which are then stored in the replay buffer, thus allowing us to use larger batch sizes and updates at every timestep.

Finally, we also allow λ to vary over time. In practice, λ is decayed as more data is collected on the system. Intuitively, in the early stages of learning, the bias in $\hat{Q}_\theta$ dominates and hence we want to rely more on the model. A larger value of λ is appropriate as it up-weights longer horizon estimates in the blended-Q estimator. As $\hat{Q}_\theta$ estimates improve over time, a smaller λ is favorable to reduce the reliance on the approximate model.

5 Experiments

Task Details: We evaluate MPQ(λ) on simulated robot control tasks, including a complex manipulation task with a 7DOF arm and in-hand manipulation with a 24DOF anthropomorphic hand (Rajeswaran* et al., 2018) as shown in Fig. 1. For each task, we provide the agent with a biased version of simulation that is used as the dynamics model for MPC. We use Model Predictive Path Integral Control (MPPI) (Williams et al., 2017), a state-of-the-art sampling-based algorithm as our MPC algorithm throughout.

1. CartpoleSwingup: A classic control task where the agent slides a cart along a rail to swingup the pole attached via an unactuated hinge joint. Model bias is simulated by providing the agent incorrect masses of the cart and pole. The masses are set lower than the true values to make the problem harder for MPC as the algorithm will always input smaller controls than desired as also noted in Ramos et al. (2019). Initial position of cart and pole are randomized at every episode.

2. SawyerPegInsertion: The agent controls a 7DOF Sawyer arm to insert a peg attached to the end-effector into a hole at different locations on a table in front of the robot. We test the effects of inaccurate perception by simulating a sensor at the target location that provides noisy position measurements at every timestep. MPC uses a deterministic model that does not take sensor noise into account as commonly done in controls. This biases the cost of simulated trajectories, causing MPC to fail to reach the target.

3. InHandManipulation: A challenging in-hand manipulation task with a 24DOF dexterous hand from Rajeswaran* et al. (2018). The agent must align the pen with target orientation within certain tolerance for succcess. The initial orientation of the pen is randomized at every episode. Here, we simulate bias by providing larger estimates of the mass and inertia of the pen as well as friction coefficients, which causes the MPC algorithm to optimize overly aggressive policies and drop the pen.

Please refer to the Appendix A.2 for more details of the tasks and biased simulations.

Baselines: We compare MPQ(λ) against both model-based and model-free baselines - (1) MPPI with true dynamics and no value function, (2) MPPI with biased dynamics and no value function (3) Proximal Policy Optimization (PPO), a state-of-the-art model-free RL method

Learning Details: We represent the Q-function with a feed-forward neural network. We bias simulation parameters like mass or friction coefficients using the formula $m=(1+b)m_{true}$, where b is a bias-factor. We also employ a practical modification to Alg. 1 in order to speed up training times as discussed in Section 4. Instead of maintaining a large global replay-buffer and re-calculating targets for every experience tuple in a mini-batch, as done by approaches such as Bhardwaj et al. (2020); Lowrey et al. (2018), we simply query MPC for the value targets online and store them in a smaller replay-buffer. This has a similar stabilizing effect as using a frozen target network in DQN and allows us to perform updates at every timestep. For PPO, we use the publically available implementation https://rb.gy/61iarq. Refer to the Appendix A.2 for more details.

5.1 Analysis of Overall Performance

O 1. MPQ(λ) *is able to overcome model-bias in MPC for a wide range of λ values.*

Fig. 2(a) shows a comparison of MPQ(λ) with MPPI using true and biased dynamics with $b=-0.5$ and $H=64$ for various settings of λ. There exists a wide range of λ values for which MPQ(λ) can efficiently trade-off the model-bias with the bias in the learned Q-function and out-perform MPPI with biased dynamics. However, setting λ to a high value of 1.0 and 0.95, which weighs longer horizons heavily leads to poor performance as compounding effects of model bias are not being compensated for by Q_θ. Performance also begins to drop as λ decreases below 0.6. We note that MPQ(λ) also outperforms MPPI with access to the true dynamics function. This is not surprising as the learned Q-function adds global information to the optimization problem and can correct for errors in optimizing for long horizons due to large variance when using limited trajectory samples in MPPI.

O 2. *Faster convergence can be achieved by decaying λ over time.*

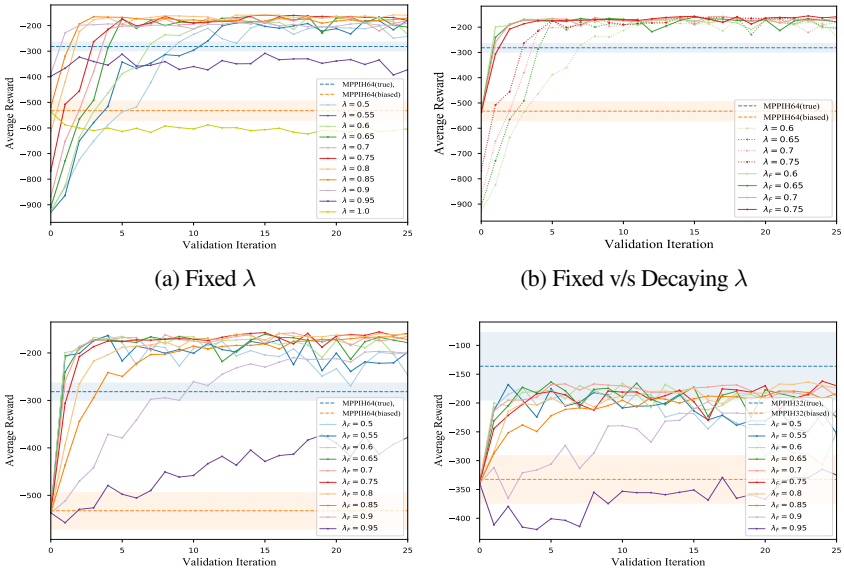
As more data is collected on the system, we expect the bias in Q_θ to decrease, whereas model bias remains constant. We decay λ in $[1.0,\lambda_F]$ using a fixed schedule to reduce the dependence on MPC over time as the model-free Q-estimates improve. This leads to faster convergence than using a fixed λ as demonstrated in Fig. 2(b). This can be attributed to the fact that during the initial steps of training, the bias in a randomly initialized Q_θ is large, whereas longer horizon lookahead with the approximate model can still lead us to good parts of the state space. Thus, initially a larger value of λ that favors longer horizons is better as the effect of Q_θ is diminished due to discounting. As more data is collected, the accuracy of Q_θ increases and bias in the model begins to hurt performance. A smaller value of λ is more favorable now as it places more weight on smaller horizon estimates. In figures 2(c) and 2(d) we present an ablation study that shows that MPQ(λ) is robust to a wide range of decay rates with $H=64$ and 32 respectively. We see that when provided with true dynamics, MPPI with $H=32$ performs better than $H=64$, which can be attributed to optimization issues with long horizons. MPQ(λ) reaches performance comparable with MPPI $H=32$ in both cases showing robustness to horizon values which is important since in practice we wish to set the horizon as large as the computation budget permits. However, decaying λ too fast or too slow can have adverse effects on performance. An interesting question for future work is whether λ can be set adaptively in a state-dependent manner. Refer to Appendix A.2 for details on decay schedule.

O 3. MPQ(λ) *is robust to large degree of model misspecification.*

Fig. 3(a) shows the effects of different values of the bias factor b to vary mass of the cart and pole for MPQ(λ) with a fixed λ decay rate of $[1.0,0.75]$. MPQ(λ) achieves better performance than MPPI ($H=64$), both with biased and true dynamics, for a wide range of bias factors b, and convergence rate is generally faster for smaller bias. For large values of b, MPQ(λ) either fails to improve or diverges as the compounding effects of model-bias hurt learning. Similarly in trend in Fig. 3(b) MPQ(λ) achieves performance comparable to MPPI with true dynamics for different degrees of bias in the mass, inertia and friction properties of the pen, but is unable to do so for $b=1.0$. Both plots show validation performance over averaged over 3 seeds. We conclude that while MPQ(λ) is robust to large amount of model bias, if the model is extremely un-informative, relying on MPC can degrade performance.

O 4. MPQ(λ) *is much more sample efficient compared to model-free RL on high-dimensional continuous control tasks, even with approximate models*

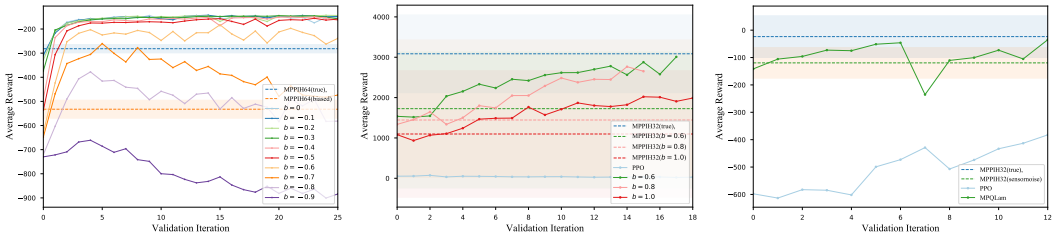
Figures 3(b) and 3(c) show comparison of MPQ(λ) with PPO (Schulman et al., 2017), a model-free policy gradient algorithm on the InHandManipulation and SawyerPegInsertion tasks respectively. In both cases, we observe that MPQ(λ), through its use of approximate models, learned value functions, and a dynamically-varying λ parameter to trade-off different sources of error, rapidly improves its



(a) Fixed λ (b) Fixed v/s Decaying λ

(c) λ decay with $H = 64$ (d) λ decay with $H = 32$

Figure 2: CARTPOLESWINGUP experiments. All curves show average rewards over 30 validation episodes, averaged over 3 runs with different seeds. Training is performed for 100k steps with validation after every 4k steps. When decaying λ as per a schedule, it is fixed to the current value during validation. In (b),(c),(d), λ_F denotes the value of λ at the end of training. The dashed lines show average reward of MPPI and shaded regions denote standard deviation.



(a) CARTPOLESWINGUP Bias Sweep (b) INHANDMANIPULATION (c) SAWYERPEGINSERTION

Figure 3: Robustness and sample efficiency of MPQ(λ). (a)Varying bias over mass of cart and pole, (b) Varying bias factor over mass, inertia and friction of pen (c) Peg insertion task with noisy perception. Same bias factor b is used for all altered properties per task. Results depict average reward over 30 validation episodes. In (a) λ is decayed in [1.0,0.75] and [1.0,0.85] in (b) and (c)

performance and achieves average reward comparable to MPPI with access to ground truth dynamics. In INHANDMANIPULATION, PPO performance does not improve at all over 54k training steps. In SAWYERPEGINSERTION, the small magnitude of reward difference between MPPI with true and biased models is due to the fact that even with a biased model, MPC is able to get the peg close to the table, but due to sensor noise, is unable to control it precisely enough to consistently insert it in the hole. Here, value function learned by MPQ(λ) can adapt to sensor noise and allow for fine-grained control near the table. PPO only marginally improves over validation iterations and does not get close to the table..

6 CONCLUSION

In this paper, we presented a method to mitigate model-bias in MPC by blending model-free estimates using a parameter λ, to trade-off different sources of bias. We present a practical algorithm that achieves performance close to MPC with access to the *true* dynamics while being sample efficient compared to model-free RL methods. However, a few key questions remain. Although faster convergence can be achieved by decaying λ over time, an interesting avenue for future research is to vary λ in a state-adaptive fashion. In particular, reasoning about the model and value function uncertainty may allow us to vary λ to rely more or less on our model in certain parts of the state space. Another interesting avenue for research is to investigate variance reduction by using λ similarly to TD(λ), allowing us to optimize longer sampling-based MPC horizons with fewer samples.

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A Appendix

A.1 Proofs

We present upper-bounds on performance of a greedy policy when using approximate value functions and models. We also analyze the case of finite horizon planning with an approximate dynamics model and terminal value function which can be seen as a generalization of (Sun et al., 2018). For simplicity, we switch to using $\hat{V}(s)$ to the learnt model-free value function (instead of $\hat{Q}(s)$)

Let $\hat{V}(s)$ be an ϵ-approximation $\left|\left|\hat{V}(s)-V^{\pi^*}_{\mathcal{M}}(s)\right|\right|_\infty \leq \epsilon$. Let MDP $\hat{\mathcal{M}}$ be an α-approximation of $\mathcal{M}$ such that $\forall(s,a)$, we have $\left|\left|\hat{P}(s'|s,a)-P(s'|s,a)\right|\right|_1 \leq \alpha$ and $|\hat{c}(s,a)-c(s,a)| \leq \alpha$.

A.1.1 A Gentle Start: Bound on Performance of 1-Step Greedy Policy

Theorem A.1. *Let the one-step greedy policy be*

$$\hat{\pi}(s) = \underset{a\in\mathcal{A}}{\operatorname{argmin}}\, \hat{c}(s,a)+\gamma\Sigma_{s'}\hat{P}(s'|s,a)\hat{V}(s') \tag{14}$$

The performance loss of $\hat{\pi}(s)$ w.r.t optimal policy π^* on MDP $\mathcal{M}$ is bounded by

$$\left|\left|V^{\hat{\pi}}_{\mathcal{M}}(s)-V^{\pi^*}_{\mathcal{M}}(s)\right|\right|_\infty \leq \frac{2\left(\gamma\epsilon+\alpha+\gamma\alpha\left(\frac{V_{\max}-V_{\min}}{2}\right)\right)}{1-\gamma} \tag{15}$$

Proof. From (14) we have $\forall s \in \mathcal{S}$

$$\hat{c}(s,\hat{\pi}(s))+\gamma\sum_{s'}\hat{P}(s'|s,\hat{\pi}(s))\hat{V}(s')\leq\hat{c}(s,\pi^*(s))+\gamma\sum_{s'}\hat{P}(s'|s,\pi^*(s))\hat{V}(s')$$

$$\hat{c}(s,\hat{\pi}(s))-\hat{c}(s,\pi^*(s))\leq\gamma\left(\sum_{s'}\hat{P}(s'|s,\pi^*(s))\hat{V}(s')-\sum_{s'}\hat{P}(s'|s,\hat{\pi}(s))\hat{V}(s')\right)$$

(using $\left|\left|\hat{V}(s)-V^{\pi^*}_{\mathcal{M}}(s)\right|\right|_\infty\leq\epsilon$)

$$\hat{c}(s,\hat{\pi}(s))-\hat{c}(s,\pi^*(s))\leq\gamma\left(\sum_{s'}\hat{P}(s'|s,\pi^*(s))V^{\pi^*}_{\mathcal{M}}(s')-\sum_{s'}\hat{P}(s'|s,\hat{\pi}(s))V^{\pi^*}_{\mathcal{M}}(s')\right)+2\gamma\epsilon$$

(using $|\hat{c}(s,a)-c(s,a)|\leq\alpha$)

$$c(s,\hat{\pi}(s))-c(s,\pi^*(s))\leq 2\gamma\epsilon+2\alpha+\gamma\left(\sum_{s'}\hat{P}(s'|s,\pi^*(s))V^{\pi^*}_{\mathcal{M}}(s')-\sum_{s'}\hat{P}(s'|s,\hat{\pi}(s))V^{\pi^*}_{\mathcal{M}}(s')\right) \tag{16}$$

Now, let s be the state with the max loss $V^{\hat{\pi}}_{\mathcal{M}}(s)-V^{\pi^*}_{\mathcal{M}}(s)$,

$$V^{\hat{\pi}}_{\mathcal{M}}(s)-V^{\pi^*}_{\mathcal{M}}(s)=c(s,\hat{\pi})-c(s,\pi^*)+\gamma\sum_{s'}\Big(P(s'|s,\hat{\pi})V^{\hat{\pi}}_{\mathcal{M}}(s')-P(s'|s,\pi^*)V^{\pi^*}_{\mathcal{M}}(s')\Big)$$

Substituting from (16)

$$\begin{aligned}V^{\pi^*}_{\mathcal{M}}(s)-V^{\hat{\pi}}_{\mathcal{M}}(s)\leq 2\gamma\epsilon+2\alpha&+\gamma\sum_{s'}\hat{P}(s'|s,\pi^*(s))V^{\pi^*}_{\mathcal{M}}(s')-\gamma\sum_{s'}\hat{P}(s'|s,\hat{\pi}(s))V^{\pi^*}_{\mathcal{M}}(s')\\&-\gamma\sum_{s'}P(s'|s,\pi^*)V^{\pi^*}_{\mathcal{M}}(s')+\gamma\sum_{s'}P(s'|s,\hat{\pi})V^{\hat{\pi}}_{\mathcal{M}}(s')\end{aligned}$$

Add and subtract $\gamma\sum_{s'}P(s'|s,\hat{\pi})V^{\pi^*}_{\mathcal{M}}(s')$ and re-arrange

$$\begin{aligned}V^{\pi^*}_{\mathcal{M}}(s)-V^{\hat{\pi}}_{\mathcal{M}}(s)&\leq 2\gamma\epsilon+2\alpha+\gamma\sum_{s'}\Big(\hat{P}(s'|s,\pi^*)-P(s'|s,\pi^*)\Big)V^{\pi^*}_{\mathcal{M}}(s')\\&\quad-\gamma\sum_{s'}\Big(\hat{P}(s'|s,\hat{\pi})-P(s'|s,\hat{\pi})\Big)V^{\pi^*}_{\mathcal{M}}(s')\\&\quad+\gamma\sum_{s'}P(s'|s,\hat{\pi})\Big(V^{\hat{\pi}}_{\mathcal{M}}(s')-V^{\pi^*}_{\mathcal{M}}(s')\Big)\\&\leq 2\gamma\epsilon+2\alpha+2\gamma\alpha\left(\frac{V_{\max}-V_{\min}}{2}\right)+\gamma\sum_{s'}P(s'|s,\hat{\pi})\Big(V^{\hat{\pi}}_{\mathcal{M}}(s')-V^{\pi^*}_{\mathcal{M}}(s')\Big)\end{aligned}$$

Since s is the state with largest loss

$$\begin{aligned}\left|\left|V^{\pi^*}_{\mathcal{M}}(s)-V^{\hat{\pi}}_{\mathcal{M}}(s)\right|\right|_\infty&\leq 2\gamma\epsilon+2\alpha+2\gamma\alpha\left(\frac{V_{\max}-V_{\min}}{2}\right)+\gamma\sum_{s'}P(s'|s,\hat{\pi})\left|\left|V^{\pi^*}_{\mathcal{M}}(s)-V^{\hat{\pi}}_{\mathcal{M}}(s)\right|\right|_\infty\\&\leq 2\gamma\epsilon+2\alpha+2\gamma\alpha\left(\frac{V_{\max}-V_{\min}}{2}\right)+\gamma\left|\left|V^{\pi^*}_{\mathcal{M}}(s)-V^{\hat{\pi}}_{\mathcal{M}}(s)\right|\right|_\infty\end{aligned}$$

Re-arranging terms we get

$$\left|\left|V^{\pi^*}_{\mathcal{M}}(s)-V^{\hat{\pi}}_{\mathcal{M}}(s)\right|\right|_\infty\leq\frac{2\big(\gamma\epsilon+\alpha+\gamma\alpha\big(\frac{V_{\max}-V_{\min}}{2}\big)\big)}{1-\gamma} \tag{17}$$

which concludes the proof. □

A.1.2 BOUND ON PERFORMANCE OF H-STEP GREEDY POLICY

Notation: For brevity let us define the following macro,

$$\langle V,\pi,\mathcal{M}\rangle_H = \mathbb{E}_{\mu^{\pi}_{\mathcal{M}}}\left[\sum_{i=0}^{H-1}\gamma^i c(s_i,a_i)+\gamma^H V(s_H)\right] \tag{18}$$

which represents the expected cost achieved when executing policy π on $\mathcal{M}$ using V as the terminal cost. We can substitute different policies, terminal costs and MDPs. For example, $\left\langle \hat{V},\hat{\pi},\hat{\mathcal{M}}\right\rangle_H$ is the expected cost obtained by running policy $\hat{\pi}$ on simulator $\hat{\mathcal{M}}$ for H steps with approximate learned terminal value function $\hat{V}$.

Lemma A.1. *For a given policy π, the optimal value function $V^{\pi^*}_{\mathcal{M}}$ and MDPs $\mathcal{M},\hat{\mathcal{M}}$ the following performance difference holds*

$$\left|\left|\left\langle V^{\pi^*}_{\mathcal{M}},\pi,\mathcal{M}\right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi,\hat{\mathcal{M}}\right\rangle_H\right|\right|_\infty \leq \gamma\left(\frac{1-\gamma^{H-1}}{1-\gamma}\right)\alpha H\left(\frac{c_{\max}-c_{\min}}{2}\right)+\gamma^H\alpha H\left(\frac{V_{\max}-V_{\min}}{2}\right)+\frac{1-\gamma^H}{1-\gamma}\alpha$$

Proof. We temporarily introduce a new MDP $\mathcal{M}'$ that has the same cost function as a $\mathcal{M}$, but transition function of $\hat{\mathcal{M}}$

$$\begin{aligned}\left\langle V^{\pi^*}_{\mathcal{M}},\pi,\mathcal{M}\right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi,\hat{\mathcal{M}}\right\rangle_H &= \left\langle V^{\pi^*}_{\mathcal{M}},\pi,\mathcal{M}\right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi,\mathcal{M}'\right\rangle_H \\ &+ \left\langle V^{\pi^*}_{\mathcal{M}},\pi,\mathcal{M}'\right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi,\hat{\mathcal{M}}\right\rangle_H\end{aligned} \tag{19}$$

Let $\Delta P(s_0...s_H) = P(s_0...s_H) - \hat{P}(s_0...s_H)$ represent the difference in distribution of states encountered by executing π on $\mathcal{M}$ and $\hat{\mathcal{M}}$ respectively starting from state s_0.

Expanding the RHS of (19)

$$= \sum_{s_0,\ldots,s_H}\Delta P(s_0...s_H)\left(\sum_{i=0}^{H-1}\gamma^i c(s_i,a_i)+\gamma^H V^{\pi^*}_{\mathcal{M}}(s_H)\right)+\mathbb{E}_{\mu^{\pi}_{\hat{\mathcal{M}}}}\left[\sum_{i=0}^{H-1}\gamma^i(c(s_i,a_i)-\hat{c}(s_i,a_i))\right] \tag{20}$$

Since the first state s_1 is the same

$$\begin{aligned}&= \sum_{s_1,\ldots,s_H}\Delta P(s_1...s_H)\left(\sum_{i=1}^{H-1}\gamma^i c(s_i,a_i)+\gamma^H V^{\pi^*}_{\mathcal{M}}(s_H)\right)+\mathbb{E}_{\mu^{\pi}_{\hat{\mathcal{M}}}}\left[\sum_{i=0}^{H-1}\gamma^i(c(s_i,a_i)-\hat{c}(s_i,a_i))\right] \\ &\leq \left|\left|\sum_{s_1,\ldots,s_H}\Delta P(s_1...s_H)\left(\sum_{i=1}^{H-1}\gamma^i c(s_i,a_i)+\gamma^H V^{\pi^*}_{\mathcal{M}}(s_H)\right)\right|\right|_\infty + \left|\left|\mathbb{E}_{\mu^{\pi}_{\hat{\mathcal{M}}}}\left[\sum_{i=0}^{H-1}\gamma^i(c(s_i,a_i)-\hat{c}(s_i,a_i))\right]\right|\right|_\infty \\ &\leq \left|\left|\sum_{s_1,\ldots,s_H}\Delta P(s_1...s_H)\left(\sum_{i=1}^{H-1}\gamma^i c(s_i,a_i)+\gamma^H V^{\pi^*}_{\mathcal{M}}(s_H)\right)\right|\right|_\infty + \frac{1-\gamma^H}{1-\gamma}\alpha\end{aligned} \tag{21}$$

where the first inequality is obtained by applying the triangle inequality and the second one is obtained by applying triangle inequality followed by the upper bound on the error in cost-function.

$$\leq \left|\left|\sum_{s_2,\ldots,s_{H+1}}\Delta P(s_2...s_{H+1})\right|\right|_\infty \sup\left(\sum_{i=1}^{H-1}\gamma^i c(s_i,a_i)+\gamma^H V^{\pi^*}_{\mathcal{M}}(s_H)-K\right)+\frac{1-\gamma^H}{1-\gamma}\alpha \tag{22}$$

By choosing $K = \sum_{i=1}^{H-1}\gamma^i(c_{\max}+c_{\min})/2+\gamma^H(V_{\max}+V_{\min})/2$ we can ensure that the term inside $\sup$ is upper-bounded by $\gamma(1-\gamma^{H-1})/(1-\gamma)((c_{\max}-c_{\min})/2)+\gamma^H(V_{\max}-V_{\min})/2$

$$\leq \gamma\left(\frac{1-\gamma^{H-1}}{1-\gamma}\right)\alpha H\left(\frac{c_{\max}-c_{\min}}{2}\right)+\gamma^H\alpha H\left(\frac{V_{\max}-V_{\min}}{2}\right)+\frac{1-\gamma^H}{1-\gamma}\alpha \tag{23}$$

□

The above lemma builds on similar results in (Kakade et al., 2003; Abbeel & Ng, 2005; Ross & Bagnell, 2012).

We are now ready to prove our main theorem, i.e. the performance bound of an MPC policy that uses an approximate model and approximate value function.

Proof of Theorem 3.1

Proof. Since, $\hat{\pi}$ is the greedy policy when using $\hat{\mathcal{M}}$ and $\hat{V}$,

$$\begin{aligned} \left\langle \hat{V},\hat{\pi},\hat{\mathcal{M}} \right\rangle_H &\leq \left\langle \hat{V},\pi^*,\hat{\mathcal{M}} \right\rangle_H \\ \left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\hat{\mathcal{M}} \right\rangle_H &\leq \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\hat{\mathcal{M}} \right\rangle_H + 2\gamma^H \epsilon \text{ (using } \left\| \hat{V} - V^{\pi^*}_{\mathcal{M}} \right\|_1 \leq \epsilon) \end{aligned} \tag{24}$$

Also, we have

$$\begin{aligned} \left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\mathcal{M} \right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\mathcal{M} \right\rangle_H = &\left(\left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\mathcal{M} \right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\hat{\mathcal{M}} \right\rangle_H \right) \\ &- \left(\left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\mathcal{M} \right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\hat{\mathcal{M}} \right\rangle_H \right) \\ &+ \left(\left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\hat{\mathcal{M}} \right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\hat{\mathcal{M}} \right\rangle_H \right) \end{aligned} \tag{25}$$

The first two terms can be bounded using Lemma A.1 and the third term using Eq. (24) to get

$$\begin{aligned} &\left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\mathcal{M} \right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\mathcal{M} \right\rangle_H \\ &\leq 2\left(\gamma \frac{1-\gamma^{H-1}}{1-\gamma} \alpha H \left(\frac{c_{\max} - c_{\min}}{2} \right) + \gamma^H \alpha H \left(\frac{V_{\max} - V_{\min}}{2} \right) + \frac{1-\gamma^H}{1-\gamma} \alpha + \gamma^H \epsilon \right) \end{aligned} \tag{26}$$

Now, let s be the state with max loss $V^{\hat{\pi}}_{\mathcal{M}}(s) - V^{\pi^*}_{\mathcal{M}}(s)$

$$\begin{aligned} V^{\hat{\pi}}_{\mathcal{M}}(s) - V^{\pi^*}_{\mathcal{M}}(s) &= \langle V^{\hat{\pi}}_{\mathcal{M}},\hat{\pi},\mathcal{M} \rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\mathcal{M} \right\rangle_H \\ &= \left(\langle V^{\hat{\pi}}_{\mathcal{M}},\hat{\pi},\mathcal{M} \rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\mathcal{M} \right\rangle_H \right) + \left(\left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\mathcal{M} \right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\mathcal{M} \right\rangle_H \right) \\ &= \gamma^H \left(V^{\hat{\pi}}_{\mathcal{M}}(s_{H+1}) - V^{\pi^*}_{\mathcal{M}}(s_{H+1}) \right) + \left(\left\langle V^{\pi^*}_{\mathcal{M}},\hat{\pi},\mathcal{M} \right\rangle_H - \left\langle V^{\pi^*}_{\mathcal{M}},\pi^*,\mathcal{M} \right\rangle_H \right) \\ &\leq \gamma^H \left(V^{\hat{\pi}}_{\mathcal{M}}(s) - V^{\pi^*}_{\mathcal{M}}(s) \right) \\ &+ 2\left(\frac{\gamma(1-\gamma^{H-1})}{1-\gamma} \alpha H \left(\frac{c_{\max} - c_{\min}}{2} \right) + \gamma^H \alpha H \left(\frac{V_{\max} - V_{\min}}{2} \right) + \frac{1-\gamma^H}{1-\gamma} \alpha + \gamma^H \epsilon \right) \end{aligned} \tag{27}$$

where last inequality comes from applying Eq. (26) and the fact that s is the state with max loss. The final expression follows from simple algebraic manipulation. □

A.1.3 Optimal Planning Horizon

Proof of Theorem 3.2

Proof. We take the derivative of (4) and set them to 0. For convenience, we define the following interim terms

$$\begin{aligned} C_1 &= \frac{\alpha}{1-\gamma} \frac{c_{\max} - c_{\min}}{2} \\ C_2 &= \alpha \frac{V_{\max} - V_{\min}}{2} \end{aligned} \tag{28}$$

The derivative is then

$$C_1\frac{\gamma^{2H}+\gamma^H((\gamma-1)H\log\gamma-\gamma-1)+\gamma}{(1-\gamma^H)^2}+C_2\frac{\gamma^H(-\gamma^H+H\log\gamma+1)}{(1-\gamma^H)^2}+\epsilon\frac{\gamma^H\log\gamma}{(1-\gamma^H)^2}=0$$
$$C_1(\gamma^{2H}+\gamma^H((\gamma-1)H\log\gamma-\gamma-1)+\gamma)+C_2(\gamma^H(-\gamma^H+H\log\gamma+1))+\epsilon(\gamma^H\log\gamma)=0 \tag{29}$$

Let $\gamma=1-\delta$ where $\delta\ll 1$. Hence $\gamma^H=(1-\delta)^H\approx 1-H\delta$. Plugging into (29),

$$\begin{aligned}&C_1((1-2\delta H)+(1-\delta H)((\gamma-1)H\log\gamma-\gamma-1)+\gamma)+\\&C_2((1-\delta H)(-(1-\delta H)+H\log\gamma+1))+\epsilon\log\gamma(1-H\delta)=0\end{aligned} \tag{30}$$

$$\begin{aligned}&C_1(H^2(1-\gamma)\delta\log\gamma-H(1-\gamma)(\delta+\log\gamma))\\&+C_2(-H^2(\delta^2+\delta\log\gamma)+H(\delta+\log\gamma))+\epsilon\log\gamma(1-H\delta)=0\end{aligned} \tag{31}$$

Using $\log\gamma=\log(1-\delta)\approx-\delta-\frac{1}{2}\delta^2$

$$\begin{aligned}C_1(-H^2\delta^3+H(\frac{1}{2}\delta^3))+C_2(H^2(\delta^3/2)+H(-\delta^2/2))+H\epsilon(\delta^2)-\epsilon\delta=0\\C_1(-H^2\delta^2+H(\frac{1}{2}\delta^2))+C_2(H^2(\delta^2/2)+H(-\delta/2))+H\epsilon(\delta)-\epsilon=0\\H^2\delta^2(C_2/2-C_1)+H\delta(\epsilon+C_2/2)-\epsilon=0\end{aligned} \tag{32}$$

For simplicity, let's assume $C_1\approx C_2/2$. Solving for the optimal H we get

$$H=\frac{\epsilon}{\delta(\epsilon+C_2/2)} \tag{33}$$

□

A.1.4 Optimal Blending Parameter

Proof of Corollary 3.1 We make a similar argument as Schulman et al. (2015). Compare the objective of unblended MPC

$$Q_H^{\phi}(s,a)=\mathbb{E}_{\mu_{\mathcal{M}}^{\pi_\phi}}\left[\hat{Q}(s_0,a_0)+\sum_{i=0}^{H-1}\gamma^i A(s_i,a_i)\,|\,s_0=s_t\right] \tag{34}$$

and the blended variant

$$Q_H^{\lambda}(s,a)=\mathbb{E}_{\mu_{\mathcal{M}}^{\pi_\phi}}\left[\hat{Q}(s_0,a_0)+\sum_{i=0}^{H-1}(\gamma\lambda)^i A(s_i,a_i)\right] \tag{35}$$

The blended variant is simply setting a steeper discount $(\gamma\lambda)$. This steeper discount results in an effective horizon of $H\approx\frac{1}{1-\gamma\lambda}$. The effect of terms beyong this H is neglible.

Hence the effect of achieving any critical H^* can be obtained by simply setting $\lambda^* such that$

$$\begin{aligned}H^*&=\frac{1}{1-\gamma\lambda^*}\\\lambda^*&=\frac{1}{\gamma}\left(1-\frac{1}{H^*}\right)\end{aligned} \tag{36}$$

A.2 EXPERIMENT DETAILS

A.2.1 TASK DETAILS

CARTPOLESWINGUP

- Reward function: $x_{cart}^2 + \theta_{pole}^2 + 0.01 v_{cart} + 0.01 \omega_{pole} + 0.01 a^2$
- Observation: $[x_{cart}, \theta_{pole}, v_{cart}, \omega_{pole}]$ (4 dim)

SAWYERPEGINSERTION We simulate sensor noise by placing a simulated position sensor at the target location in the MuJoCo physics engine that adds Gaussian noise with $\sigma = 4$cm to the observed 3D position vector. MPPI uses a deterministic model that does not take sensor noise into account for planning.

- Reward function: $-1.0 * ||x_{ee} - x_{target}||_1 - 5.0 * ||x_{ee} - x_{target||_2} + 5 * \mathbb{1}(||x_{ee} - x_{target}||_2 < 0.06)$
- Observation: $\left[q_{pos}, q_{vel}, x_{ee}, x_{target}, x_{ee} - x_{target}, ||x_{ee} - x_{target}||_1, ||x_{ee} - x_{target||_2}\right]$ (25 dim)

INHANDMANIPULATION

- Reward function: $-||x_{obj} - x_{des}||_2 + z_{obj}^T z_{des} +$ Bonus for proximity to desired pos + orien, $z_{obj}^T z_{des}$ represents dot product between object axis and target axis to measure orientation similarity.
- Observation: $[q_{pos}, x_{obj}, v_{obj}, z_{obj}, z_{des}, x_{obj} - x_{des}, z_{obj} - z_{des}]$ (45 dim)

A.2.2 LEARNING DETAILS

Here we present details of the learning setup and parameters used. All parameters were found using a coarse grid search and better settings might exist.
MPQ(λ): For all tasks, we represent Q function using 2 layered fully-connected neural network with 100 units in each layer and ReLU activation. We use ADAM (Kingma & Ba, 2014) for optimization with a learning rate of 0.001 and discount factor $\gamma = 0.99$. Further, the buffer size is 1500 for CARTPOLESWINGUP and 3000 for the others, with batch size of 64 for all.
λ **Decay**: In all our experiments, we decay λ according to the following sublinear decay rate to smoothly decay λ over time

$$\lambda_t = \frac{\lambda_0}{1 + \kappa\sqrt{t}} \tag{37}$$

where the decay rate κ is calculate based on the desired final value of λ.

PPO: Both policy and value functions are represented by feed forward networks with 2 layers each with 64 and 128 units for policy and value respectively. All other parameters are left to the default values. Teh number of trajectories collected per iteration is modified to correspond with the same number of samples collected between validation iterations for MPQ(λ).

MPPI parameters Tables A.2.2, 2, 3 show the MPPI parameters used for different experiments. In addition to the standard MPPI parameters, in certain cases we also use a step size parameter as introduced by Wagener et al. (2019). For INHANDMANIPULATION and SAWYERPEGINSERTION we also apply autoregressive filtering on the sampled MPPI trajectories to induce smoothness in the sampled actions, with tuned filter coefficients. This has been found to be useful in prior works (Summers et al., 2020; Lowrey et al., 2018) for getting MPQ(λ) to work on high dimensional control tasks.

Table 1: CARTPOLESWINGUP

Parameter	Value
Horizon	32
Num particles	60
Covariance (Σ)	0.45
Temperature(β)	0.1
Filter coeffs	[1.0, 0.0, 0.0]
Step size	1.0

Table 2: SAWYERPEGINSERTION

Parameter	Value
Horizon	32
Num particles	120
Covariance (Σ)	0.1
Temperature(β)	0.005
Filter coeffs	[0.25, 0.8, 0.0]
Step size	0.9
γ	0.99

Table 3: INHANDMANIPULATION

Parameter	Value
Horizon	32
Num particles	100
Covariance (Σ)	0.3
Temperature(β)	0.15
Filter coeffs	[0.25, 0.8, 0.0]
Step size	1.0
γ	0.99