Review on MPC and learning in general

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November 2021

Model predictive is a control strategy that is mainly based on two elements:

- A model of the system to control
- An optimizer that solves a problem making use of the model .

Researches on integrating Model predictive control and learning by and large aim at reducing the the time constraints that comes with utilizing MPC in fast dynamic online systems. This is done through three different strategies:

- Replace the system model by a learning algorithm. The goal here is to learn the system dynamic in order to construct the plant model based on data;
- Replace the optimization by a learning algorithm. This strategy aims at using use a learning algorithm to approximate the MP control law.
- MPC for safe learning: The third direction is to derive safety guarantees for learning-based controllers. The main idea is to decouple the optimization from the requirement of constraints satisfaction which can be addressed using MPC techniques;
- Bypass Both component of the MPC by a learning algorithm that used data collected via the simulation of a well design model predictive controller using either Reinforcement learning or supervised learning

1 Learning the system dynamics

In [AAS21] it has been proposed a methodology to integrate Economic MPC (EMPC) and RL for online model parameter estimation of a class of nonlinear systems. In this framework, the RL agent continuously compares the measured state of the process with the model's predictions in order to adapt by modifying the model parameters accordingly. The EMPC operates the closed loop system based on the updated model prediction.

The authors in [LKS15] described a novel deep architecture for physical prediction for complex tasks such as food cutting. When the resulting model is used in a predictive framework, it yields a DeepMPC controller which is able to learn task-specific controls.

The authors in [Pic+00] proposed to approximate a non linear system dynamics that is with NN and an MPC is applied later using the learned system

2 Approximating the MPC law

The authors in [Kar+20] proposed a methodology to extend the work of [HFH20; Low+19] by learning to solve tasks defined by simple and easily interpretable high level objectives on a real unmanned ground vehicle (UGV). The presented method is mainly based off the actor-critic framework. The actor is represented by a non-linear model predictive controller while the critic captures the global value function represented by a NN. The extenxion proposed lie in the fact that, to solve the MPC problem, [HFH20; Low+19] used a model predictive path integral formulation while here, the authors MPC problem used a sequential quadratic programming formulation due to its ability to handle state-input constraints

In [Wil+17] the authors proposed a multilayer neural networks to approximate the system dynamics, and demonstrate the ability of model predictive path integral to perform difficult real time control tasks using the approximate system model.

In [Mas+20], the authors present a semi-explicit formulation of MPC for hybrid systems with feasibility guarantee. The formulation aims at reducing the computational requirements of hybrid MP controllers applied to micro-grid. This is achieved using ML techniques to learn a map from the realization of the parameters of the optimization problem to corresponding optimal binary solutions. The resulting binary variable are then used to transform the original mixed integer linear programming problem to a linear program.

3 Safe Learning

The authors in [Lub+20] combine the strength of RL and MPC in the same framework that is Control for On-Ramp Merging. Through simulation, it has been showed that the RL algorithm can merge more efficiently and smoothly but without safety guarantee that MPC automatically handles. The MPC is therefore used as supervisor such that it evaluates the RL proposed trajectory and takes control by applying the control of its predicted trajectory when the RL's is unsafe.

In [Hew+20], a methodology is proposed to use any learning based controller combine with the so called model predictive safety filter. Its role is to check if the proposed learning control leads to a state where a predefined safety set is attainable. If this condition is checked the proposed learning control is directly applied to the system. In the contrary, the model predictive safety filter modifies as little as possible the learning control by solving an optimization problem under the constraints of a reachable safety set.

4 Bypass Both MPC components

The authors in [Kum+18] proposed a neural network (DNN) controller trained offline in order to replace a well design MPC controller with application in the control of the moisturize content of a paper making machine. To ensure generalization of the NN to complex process, a deep NN (DNN) architecture is used. The deep architecture uses past control actions to capture temporal relations between control actions while the NN uses current system output and target system output to predict the control actions.

In [Drg+18] it has been proposed a compact methodology to construct a simple sub-optimal MPC-like control strategies for building control applications by using advanced machine learning algorithms. They focus on the creation of a systematic and universal framework applicable to a variety of large-scale building control problems, while giving insights on how to select the most relevant features and appropriate type of approximation model. In order to accomplish this, the authors make use of regression tree where the approximation is given as a binary tree and time delay NN with deep architecture which acts as universal approximators for time series problems

The data generation for the NN training propossed in [Drg+18] is improved in [Mor+18] by combining a design of experiments methods. The improved strategy is applied to the control of a real time Diesel engine air path system.

Not read Yet in depth : Using RL [Dor+21; GCD21],

[ZGB19] : Two cases of using MPC and RL:

- Use MPC as a function approximator within RL
- Frame tuning MPC's parameters as a non linear function approximator parameters

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