Anticipative Model Predictive Control using Gaussian Processes

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Model predictive control (MPC) is a prime control approach for handling constraints on signals, it is an online control design which optimizes system performance based on predicting its future behaviour over a so-called *prediction horizon* (N).

For practical implementation, MPC based on *linear parameter-varying* (LPV) models is considered for controlling nonlinear plants, where nonlinearities are embedded in a so-called *scheduling parameter* (p), which are employed online to compensate these nonlinearities, see Fig. 1. However, the main difficulty in an LPVMPC setting is the fact that only the instantaneous value $p(k)$ of the scheduling parameter is usually available for the MPC algorithm.

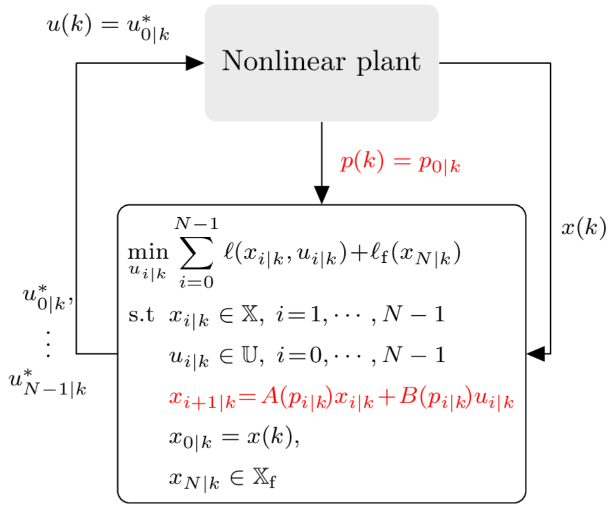

Fig. 1 Closed-loop block clock diagram, the lower block shows the online optimization problem of the LPVMPC approach. The LPV model is in red.

But its future values $p_{1|k}, p_{2|k}, \dots, p_{N|k}$ over the MPC *prediction horizon are* unknown. Several approaches have been introduced in the literature to deal with the uncertainty of $p_{1|k}, p_{2|k}, \dots, p_{N|k}$. Most of these approaches often result in very conservative LPVMPC schemes with high computational complexity. Note that the achievable control performance of an MPC design approach is related with the degree of conservatism. Consequently, one can maximize the control performance if the values of $p_{1|k}, p_{2|k}, \dots, p_{N|k}$ can be anticipated online.

The aim of this project is to investigate advanced machine learning tools in terms of *Gaussian processes* (GPs) for anticipating the scheduling parameter of the LPV models over the MPC prediction horizon. It is important to classify the problem into two classes, one when p is an exogenous variable, i.e., independent of the plant dynamics, and when p is an indigenous variable, i.e., related to the system's state. Both approaches will be investigated in this project.

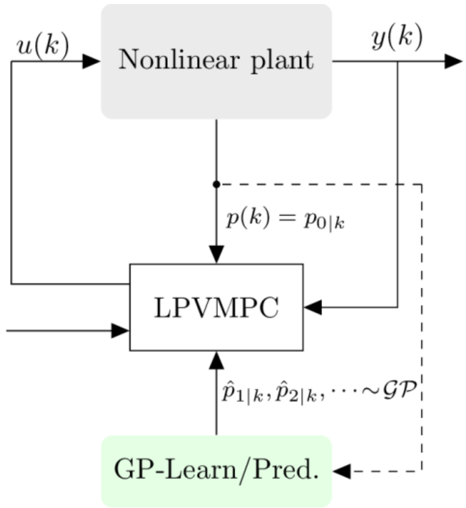

Fig. 2 LPVMPC scheme, where the future values of the scheduling parameters are anticipated by GP.

Project activities:

- Understanding the MPC/LPV/GP fundamental concepts
- Converting nonlinear dynamics into LPV representations.
- Using quadratic programming (QP) tools to solve the LPVMPC optimization problem.
- Using GP learning tools to identify the hyperparameters of a GP model for the scheduling parameter based on its available data.
- Combining GP learning/regression/prediction with the MPC to solve the anticipative LPVMPC problem
- Investigating the anticipating strategy, when the scheduling variable is exogenous or indigenous.
- Incorporating the probabilistic uncertainty of the estimated p in the anticipative LPVMPC optimization problem.
- Evaluating the GP based MPC framework from computational aspects on a benchmark control problem.

Prerequisites: Basics of automatic control, linear systems theory and signal processing.