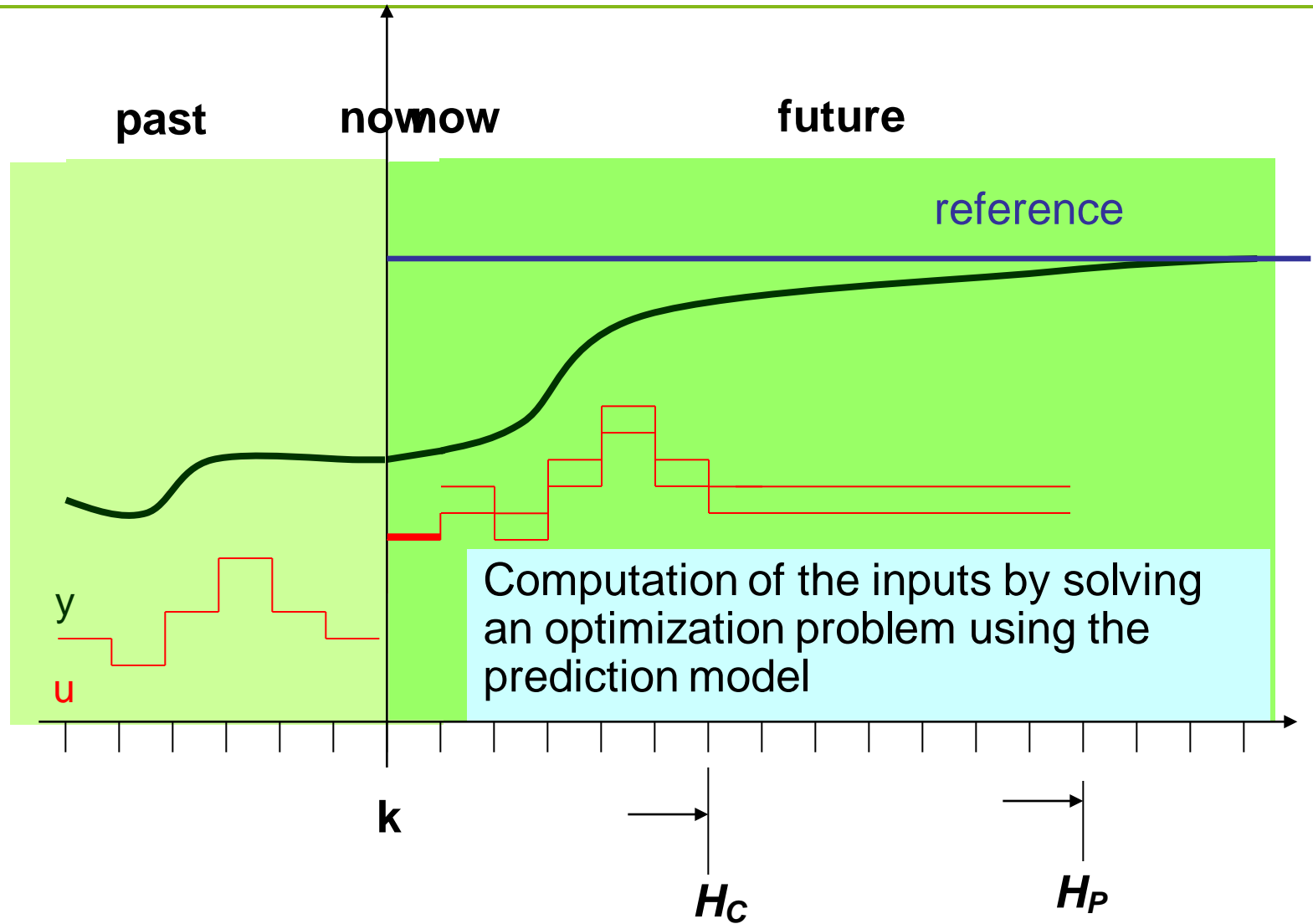


Model Predictive Control

Model Predictive Control



Features

- Open-loop optimization instead of feedback control
- Based upon a plant model, a number of future inputs are optimized such that the performance over a finite (prediction) horizon is optimized
- Number of inputs considered can be smaller than the prediction horizon, following values are kept constant

- Ingredients:
 - Model
 - Cost function
 - Optimizer
 - Error feedback

History (1)

- The fathers:
 - Jacques Richalet et al. (1976, 1978)
Model-predictive heuristic control
 - Charles Cutler (Shell, first application 1973)
DMC
 - Linear impulse response or step response input/output models obtained from plant tests
 - Quadratic performance criterion
 - No constraints
- The second generation
 - **QDMC** (1983)
 - As before, but: **WITH CONSTRAINTS** on inputs and outputs
 - Online solution of a quadratic program

Typical MPC Cost Function

General cost function

$$\min_{\underline{u}} J = \sum_{j=1}^{N_p} e_{k+j}^T Q_j e_{k+j} \quad e_{k+j} = \underline{y}_{k+j}^{ref} - \hat{\underline{y}}_{k+j}$$

$$+ \sum_{j=0}^{N_i} \Delta \underline{u}_{k+j}^T S_j \Delta \underline{u}_{k+j}$$

$$+ \sum_{j=0}^{N_u} \left(\underline{u}_{k+j} - \underline{u}_{ss}^{opt} \right)^T R_j \left(\underline{u}_{k+j} - \underline{u}_{ss}^{opt} \right)$$

\underline{u}_{ss}^{opt} : optimal steady state input.

while respecting the constraints on $\underline{u}_{k+j}, \hat{\underline{y}}_{k+j}$

- Bias-update: Actual prediction error is subtracted from the reference \rightarrow steady-state accuracy for constant model error, integrating controller

More parameters / variants

- Filtering of the reference moves → desired trajectory more realistic
 - Effect similar to weights on the control moves
- Variant: Minimize the error to the reference trajectory at one point rather than minimizing the overall error
- Range control: no reference tracking but only constraints for some variables (if not critical for performance)
- Many tuning parameters, experience required
- Handling of infeasibility: dropping or softening of constraints

Stability

- Stability of classical input/output MPC schemes is not guaranteed
- Heuristic rules
 - Prediction horizon should be sufficiently long
 - Less inputs give more robust behaviour
- Plant identification is the key to success

- More recent developments
 - System identification rather than data-based models
 - Stability guarantees by use of state space models and terminal constraints / penalties of an infinite prediction horizon

Current Developments

- MPC with nonlinear models
 - Straightforward generalization from the linear case
 - Nonconvex nonlinear online optimization required
- MPC with economic cost function rather than tracking
- Robustness against plant-model mismatch
 - Minmax MPC: minimize the cost function for the worst case disturbance
 - Disturbance replaces model mismatch
 - High effort, conservative