A small step towards a systematic design of effective and implementable NMPC setting

The Python-package MPC_tuner



Mazen Alamir

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Recalls on Nonlinear Model Predictive Control (NMPC)

Real-Time considerations

Design of NMPC setting

The MPC_tuner package

Conclusion and future extensions

Recalls on Nonlinear Model Predictive Control (NMPC)

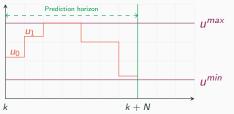
Predicted state profile $x(\cdot)$

 \forall candidate control sequence

$$\boldsymbol{u}_k := (u_0, \ldots, u_{N-1})$$

a cost can be predicted

Candidate control profile \mathbf{u}_k



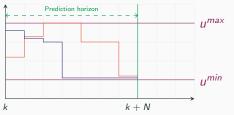
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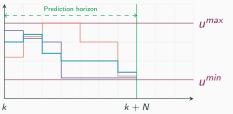
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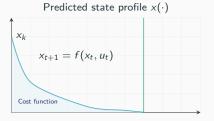
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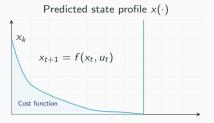
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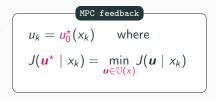
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 $J(\mathbf{u}_k \mid x_k)$

Candidate control profile \mathbf{u}_k $\begin{array}{c} & & \\$

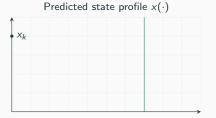


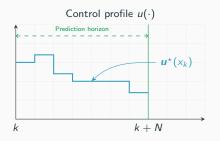


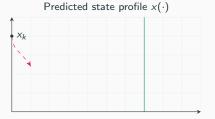


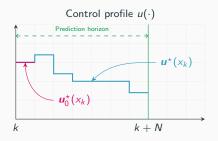


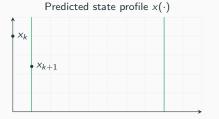


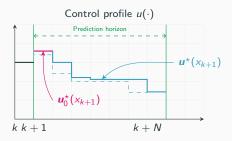


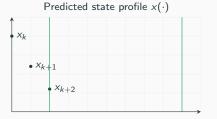




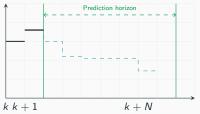




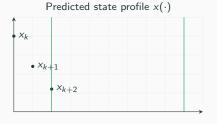








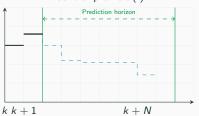
NMPC ← The Receding-horizon principle in action



- \checkmark At each updating instant
- ✓ The prediction horizon is shifted
- $\checkmark~$ A new optimization problem is defined
- $\checkmark~$ and solved

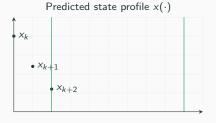
V ...

- ✓ The first action is applied
- \checkmark until the next updating instant
- \checkmark The process is repeated



Control profile $u(\cdot)$

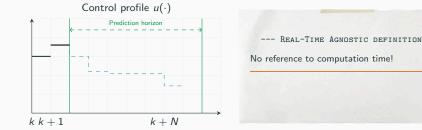
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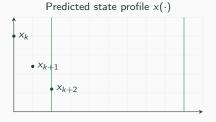
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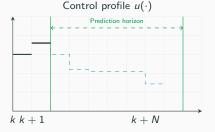
Mazen Alamir

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√ ...



--- REAL-TIME AGNOSTIC DEFINITION ---No reference to computation time! We'll come back to this later... let's first examine the optimization problem!

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$$(u_{k} = u_{0}^{\star}(x_{k}) \text{ where}$$
$$J(\boldsymbol{u}^{\star} \mid x_{k}) = \min_{\boldsymbol{u} \in \mathbb{U}(x)} J(\boldsymbol{u} \mid x_{k})$$

More precisely ...



$$\min_{\boldsymbol{u}} \left[\Psi(x_{k+N}) + \sum_{i=1}^{N} \ell(x_{k+i}, u_{k+i-1}) \right]$$
under
$$\begin{vmatrix} x_{k+N} \in \mathbb{X}_{f} \\ x_{k+i} \in \mathbb{X} \\ u_{k+i-1} \in \mathbb{U} \end{vmatrix}$$

 \dagger where Ψ is a control-Lyapunov-function inside \mathbb{X}_{f} .

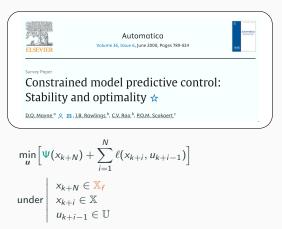


$$X \quad (\Psi, \mathbb{X}_f) \text{ almost impossible} \\ \text{to compute for real-life} \\ \text{systems}$$

X Never used outside academic toy examples!

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Don't even try!

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	based nonlinear model predictive control formulation ility-related terminal constraints*
$ \frac{\text{Mazen Alamir}}{\text{CRRS/Gloss-lab, University}} $ $ \min_{(\boldsymbol{u},q)} \begin{bmatrix} c \end{bmatrix} $	

where z is an internal state of the controller

✓ Contractive formulations

Prediction horizon is a decision variable.



Accept transient increase of the cost function

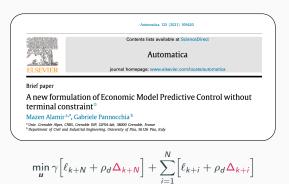
 \rightarrow multi-step Lyapunov function

NMPC ← **The formulations**

where $m \in \mathbb{N}$

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ELSEVIER		journal homepage: www.elsevier.com/locate/automatica
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	g weightir	ng profiles without terminal constraints*
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Mazen Alan	g weightir hir e Alpes, Gipsa-lab, F-3	ng profiles without terminal constraints*
Mazen Alan	g weightin hir e Alpes, Gipsa-lab, F-3 $ \min_{u} \left[\sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} $	ng profiles without terminal constraints [®]

- ✓ Enhances stability with short prediction horizons
- $\rightarrow\,$ a smoother version o f the terminal state constraints



under $\begin{vmatrix} \boldsymbol{u} \in \mathbb{U}^N \\ \boldsymbol{x}_{k+\ell} \in \mathbb{I} \end{vmatrix}$

wh

$$x_{k+\ell} \in \mathbb{A}$$

ere $\Delta_k := \|x_k - x_{k-1}\|$

- ✓ Economic MPC
- $\checkmark~$ Standard proof of stability

Does the formulation matter?





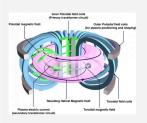


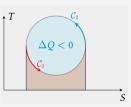


$\operatorname{QUESTION}$: Does the formulation really matter?

The impact of formulations!

Cryogenic Refrigerators - Problem statement





Source: https://www.euro-fusion.org

Why?

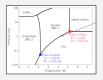
Provide refrigeration capacity to cool down the supra-conducting coils used to accelerate the plasma in Nuclear Fusion Reactors (ITER, JT60)



How?

Force a thermodynamic fluid to make a counter-clock cycle in the (S, T)=(Entropy,Temperature) plan.

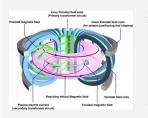
$$\int dQ = \underbrace{\int_{\mathcal{C}_1} TdS}_{>0} + \underbrace{\int_{\mathcal{C}_2} TdS}_{<<0}$$





The impact of formulations!

Cryogenic Refrigerators - Problem statement

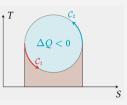


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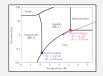


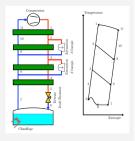


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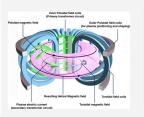
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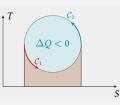


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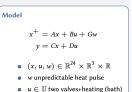


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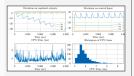
Objective

Keep the station sustainable despite of unmeasured and unpredictable w.

Cryogenic refrigerator: The impact of formulation

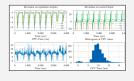
Cost function

$$\sum_{i=1}^{N} \left[\|y_{k+i}\|_{Q_{y}}^{2} + \epsilon \|x_{k+i}\|^{2} \right]$$



Cost function

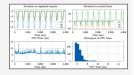
$$\sum_{i=1}^{N} \left[\|y_{k+i}\|_{Q_{y}}^{2} + \epsilon \|x_{k+i}\|^{2} \right] + \epsilon_{f} \|x_{i+N}\|^{2}$$



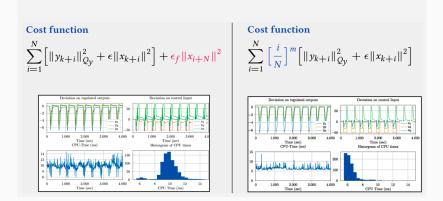
Optimization problems are solved using the GUROBI-Python-3 framework implemented on a Mac-PowerBook 2.9GHz (High Sierra OS version 10.13.3).

Cost function

$$\sum_{i=1}^{N} \left[\frac{i}{N}\right]^{m} \left[\left\|y_{k+i}\right\|_{Q_{y}}^{2} + \epsilon \left\|x_{k+i}\right\|^{2} \right]$$



Cryogenic refrigerator: The impact of formulation



Does the formulation matter?



QUESTION: Does the formulation really matter?

ANSWER: Of course!

A single parameterized formulation

$$\begin{aligned} & \text{Standard} \qquad \left[\Psi(x_{k+N}) + \sum_{i=1}^{N} \ell_{k+i} \right] & \text{s.t } c_j(x_{k+i}, u_{k+i-1}) \leq 0 \\ & \text{Economic} & \gamma \left[\ell_{k+N} + \rho_d \Delta_{k+N} \right] + \sum_{i=1}^{N} \left[\ell_{k+i} + \rho_d \Delta_{k+i} \right] & \text{s.t } c_j(x_{k+i}, u_{k+i-1}) \leq 0 \\ & \text{Variable weight} & \left[\sum_{i=1}^{N} \left[i/N \right]^m \ell(x_{k+i}, u_{k+i-1}) \right] & \text{s.t } c_j(x_{k+i}, u_{k+i-1}) \leq 0 \end{aligned}$$

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Unified structure parameterized by
$$\rho_f, \rho_d, m, \rho_{cstr}, N$$

$$\min_{u} \left[\rho_f \Psi(x_{k+N}, \rho_d \Delta_{k+N}) + \sum_{i=1}^{N} [i/N]^m [\ell_{k+i} + \rho_d \Delta_{k+i}] + \rho_{cstr} \max_{j=1}^{n_c} \lfloor c_j(x_{k+i}, u_{k+i-1}) \rfloor_+ \right]$$

How to choose the parameters of the formulation?

- $\checkmark~$ Constraints must be respected over the closed-loop trajectory
- $\checkmark\,$ Closed-loop stability should be guaranteed
- \checkmark The feedback must be <u>real-time</u> implementable

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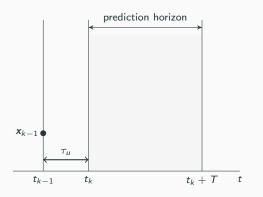
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Unified structure parameterized by
$$\rho_f$$
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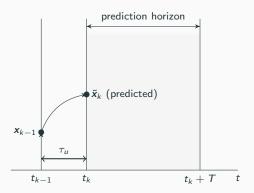
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Real-Time considerations

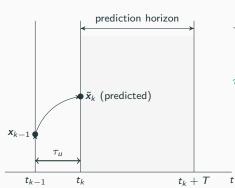


MPC: The Control Updating Period τ_u

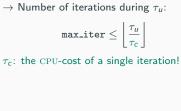
- 1. Predict \tilde{x}_k (CPU-negligible)
- 2. During $[t_{k-1}, t_k]$ Compute $\mathbf{u}^*(\tilde{\mathbf{x}}_k)$



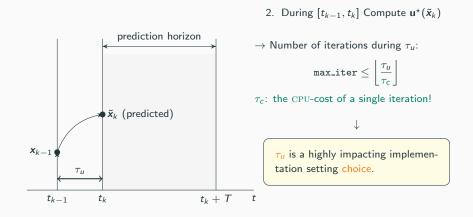
MPC: The Control Updating Period τ_u



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MPC: The Control Updating Period τ_u



1. Predict \tilde{x}_k (CPU-negligible)



- τ_u The updating period.
- au Basic sampling period[†]

 \dagger Largest τ making RK(τ) appropriate

 $\tau_{u} = \kappa \tau \qquad \kappa \in \mathbb{N}$



- τ_u The updating period.
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$$\tau_{u} = \kappa \tau \qquad \kappa \in \mathbb{N}$$



$$\rightarrow \text{use}\left(\text{n_steps} \ \times \ \text{RK}(\frac{\tau_u}{\text{n_steps}}) \right)$$



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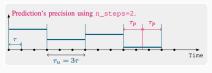
† Largest au making RK(au) appropriate

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Use reduced control horizon leading to

 $n_control \times n_u$ d.o.f.



$$\rightarrow$$
 Instead of $\kappa \times \mathtt{RK}(\tau)$,

$$\rightarrow \text{use}\left(\text{n_steps} \ \times \ \text{RK}(\frac{\tau_u}{\text{n_steps}}) \right)$$



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Use reduced control horizon leading to

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 $(\leq \left| \frac{\kappa \tau}{\tau_c} \right|)$

Choose the maximum number of iterations:

max_iter



$$\rightarrow$$
 Instead of $\kappa \times \text{RK}(\tau)$,

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Use reduced control horizon leading to

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Choose the maximum number of iterations:

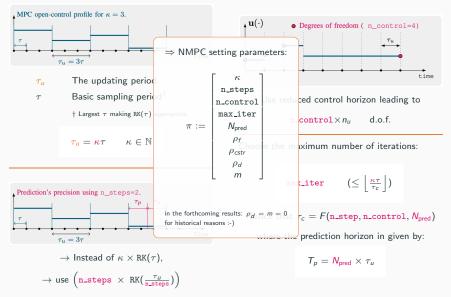
$$\max_{iter} \quad (\leq \left| \frac{\kappa \tau}{\tau_c} \right|)$$

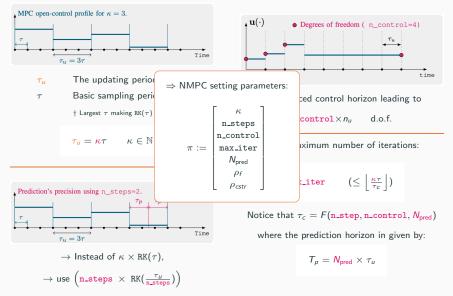
Notice that $\tau_c = F(n_step, n_control, N_{pred})$

where the prediction horizon in given by:

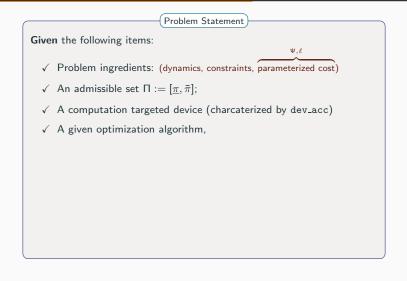
$$T_p = N_{\text{pred}} \times \tau_u$$

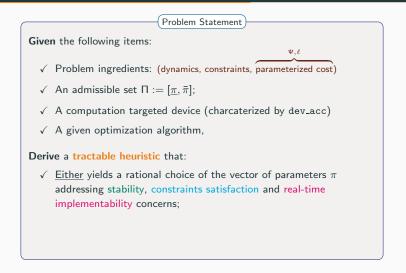
SAGIP / CT-CPNL Scientific Day, November 16th 2023, Valence, France.

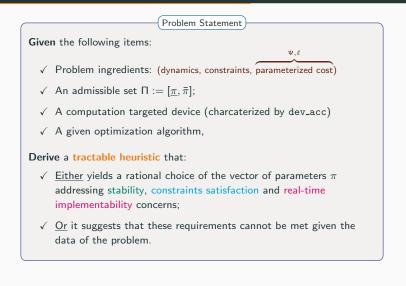


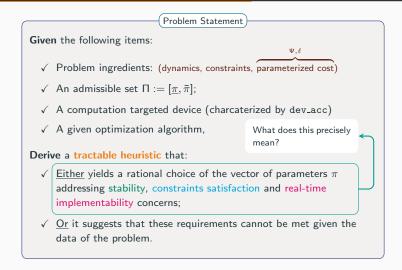


Design of NMPC setting

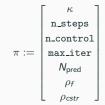








Find a design parameter vector π s.t. over a sufficiently rich set of scenarios A, an K-steps closed-loop trajectories under the π -corresponding NMPC satisfy for all $sc \in A$:



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RT-feasibility

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$\gamma\text{-}\mathsf{Contraction}$

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What is a scenario sc?

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Question 2:

What is a sufficiently rich set of scenarios $\mathcal{A}?$

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$$sc := \begin{bmatrix} x_0 \\ p \\ q \end{bmatrix}$$

- x₀ Initial state vector
- *p* Model's parameter vector
- q Exogenous/context items' vector

(set-points, observed quantities, disturbance, etc.)

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This is conditioned by:

- \checkmark An appropriate sampling of (x_0, p, q) inside their sets of possibilities
- ✓ A sufficiently high number n_samples of instances

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<pre># candidates</pre>	$\eta = 0.1$	$\eta = 0.05$	$\eta=$ 0.01	$\eta = 0.001$
1	132	264	1317	13164
5	154	308	1536	15354
10	163	326	1628	16280
100	193	386	1930	19299
1000	223	445	2225	22249

Table 1: The required card(A) as a function of the precision parameter η for a confidence parameter of $\delta = 10^{-3}$ and a number of admitted failure = 1.

The values of n_samples needed to be confident at $(1-\delta)100\%$ that the properties are satisfied with a probability greater than $(1-\eta)100\%$

[Alamo et al. Randomized strategies for probilistic solution of uncertain feasibility ans optimization problems, IEEE TAC, 2009]

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 $\pi := \begin{bmatrix} \kappa \\ \texttt{n_steps} \\ \texttt{n_control} \\ \texttt{max_iter} \\ N_{\texttt{pred}} \\ \rho_f \\ \rho_{cstr} \end{bmatrix}$

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Principle

- $\checkmark \ (\pi, \mathtt{sc}) \in \mathsf{\Pi} \times \mathcal{A} \to \mathsf{successful} \text{ or not!}$
- $\checkmark~\pi$ is eligible if successful on all sc in $\mathcal A$

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Difficulties

- \checkmark checking admissibility of $\pi \leftarrow \texttt{n_samples}$ <code>CL-simulations</code>
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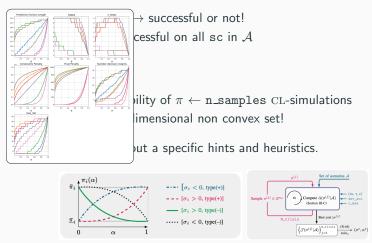
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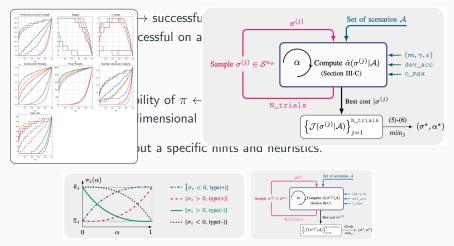
Design of NMPC setting: Principle & Difficulties

Principle



Design of NMPC setting: Principle & Difficulties

Principle



The MPC_tuner package

The MPC_tunner package: An overview

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inages	Add files via upload	5 days ago
D UCENER	Initial commit	last week
MPC_turner_py	Add files via upload	5 days ago
C READWEINS	Update README.red	5 days ago
B set_MPC_tanecipyeb	Add files via upload	5 days ago
user_defined_patchpy	Add files via upload	fi dava ana

MPC_tuner @

A python package for the optimization of NVPC implementation options

DCE 13.1281/serveds.8401011

Citation @

A full description of the principles and a detailed illustrative example are given in the paper below.

Mazzen Alamiz. A framework and a pythes -package for real-time NMPC parameter settings. artiv/2009.17238, October, 2023.

Mazen Alamir. (2028). mazenalamin/MPC_tuner: MPC_tuner (1.0). Zenodo. https://doi.org/10.5281 (penodo.8409251

Recall on Nonlinear Model Predictive Control @

Nonlinear Model Predictive Costrol (NMPC) is the most advanced central design. It enables to size into account nonlinear dynamics, non conventional costrol objective through the definition of a cost function and the presence of through the costrol accountions. It is executed to account the reportive obligation of optimal costrol problems of the following form (soft constraints are used except for the insul control extraordine):

$$\min_{\mathbf{u}} J(\mathbf{u} \mid \boldsymbol{e}_{0}, p) := \rho_{f} \Psi(\boldsymbol{x}_{N}) + \sum_{k=1}^{N_{max}} \ell(\boldsymbol{x}_{k}, \boldsymbol{u}_{k-1}) + \rho_{0kt} \max_{i=1}^{N_{max}} [c_{i}(\boldsymbol{e}_{k}, \boldsymbol{u}_{k-1})]_{+}^{2}$$

where

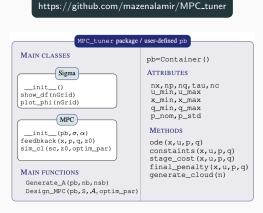
• $u := (u_0, \dots, u_{N_{point}-1}) \in [\mathbb{R}^{n_0}]^{N_{point}}$ is the sequence of control that minimizes the above cost function • x_0 are the next states a starting from the initial state x_0 and given the dynamics:

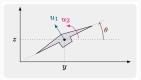
 $\dot{x} = f(x, u, p)$

https://github.com/mazenalamir/MPC_tuner

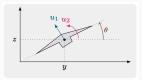
The MPC_tunner package: An overview





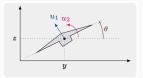


$$\begin{split} \ddot{y} &= -u_1 \sin \theta + p_1 u_2 \cos \theta \\ \ddot{z} &= u_1 \cos \theta + p_1 u_2 \sin \theta - 1 \\ \ddot{\theta} &= p_2 u_2 \end{split}$$



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$$\begin{aligned} x &:= (y, z, \theta, \dot{y}, \dot{z}, \dot{\theta}) \\ x_d &:= (q_1, q_2, 0, \dots, 0) \\ \ell &:= \|x - x_d\|_Q^2 + \|u - u_d\|_R^2 \\ \Psi &:= \rho_f \|x - x_d\|_Q \\ \gamma &:= 0.98, \\ u &\in [-50, +50]^2 \\ |\dot{\theta}| &\leq 1 \text{ and } |\theta| \leq \pi \\ \tau &= 0.02 \end{aligned}$$

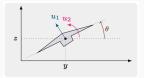


Design parameter	min-value	max-value
N_pred	5	25
κ	1	10
ρ_f	1	10^{3}
rho_cstr	10^{3}	10^{7}
max_iter	5	20

Definition of Π boundaries.

$$\ddot{y} = -u_1 \sin \theta + p_1 u_2 \cos \theta$$
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Definition of Π boundaries.

 $\ddot{z} = u_1 \cos \theta + p_1 u_2 \sin \theta - 1$ import numpy as np
from casadi import vertcat

```
\begin{aligned} x &:= (y, z, \theta, \dot{y}, \dot{z}, \dot{\theta}) \\ x_d &:= (q_1, q_2, 0, \dots, 0) \\ \ell &:= \|x - x_d\|_Q^2 + \|u - u_d\|_R^2 \\ \Psi &:= \rho_f \|x - x_d\|_Q \\ \gamma &:= 0.98, \\ u &\in [-50, +50]^2 \\ |\dot{\theta}| &\leq 1 \text{ and } |\theta| \leq \pi \\ \tau &= 0.02 \end{aligned}
```

```
class Container:
    def __init__(self):
```

pass

```
pvtol.rcontainer()
pvtol.rc, pvtol.nu = 6, 2
pvtol.rc, pvtol.nu = 6, 2
pvtol.rc, pvtol.rc, 9, 2, 4
pvtol.rc, protol.rc, 9, 2, 4
pvtol.rc, min = np.array([-5e1, -5e1])
pvtol.rc, min = np.array([-2, -2, -0.8 + np.pi, \
rvtol.rc, min = (-1, -1, 1, -0, 1, -0, 1])
pvtol.rc, max = -pvtol.rc, min
pvtol.rc, min = pvtol.p
rvtol.prom = pvtol.p
rvtol.p.std, pvtol.rc = 0.1, 0.02, 4
*-----
```

The user-defined file (part 1)

```
#-----
def p_vtol(x, u, p):
    xdot = vertcat(...)
   return xdot
£-----
def constraints(x, u, p, q):
    d_theta_dt_max, theta_max = q[2], q[3]
    c = vertcat(x[5]/d theta dt max-1,...)
   return c
£-----
def stage cost(x, u, p, q):
    return ell
#-----
def final penalty(x, p, q):
    ef = 0
    for i in range(6):
       ef += a xf[i] * (x[i] - xd[i]) ** 2
   return ef
#-----
def generate cloud(nSamples=None):
    x min. x max = pytol.x min. pytol.x max
    A sc = Container()
    A_sc.x0, A_sc.p, A_sc.q = X, P, Q
   return A sc
#-----
pvtol.ode = p vtol
pvtol.constraints = constraints
pvtol.final_penalty = final_penalty
pytol.stage cost = stage cost
pytol.generate cloud = generate cloud
```

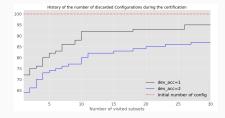
The user-defined file (part 2)

```
from user defined pytol import pytol
    from pvMPC import Design MPC. Sigma, generate A. OptimPar
    # Generate the set of scenarios
    nb. nsb = 30. 10
    A = generate_A(pvtol, nb, nsb)
    # Generate the set of candidate sigma's
    N trials = 100
    S = [Sigma() for _ in range(N_trials)]
    # Set the Design meta-parameters and run the Design
    optim_par = OptimPar(gam=0.98, c_max=0.1,
                            dev acc=1.0, T=0.5)
    R design log = Design MPC(pytol, S. A. optim par)
\gamma := 0.98.
                                             pvtol.q_min = [-1, -1, 1, np.pi]
                                             pvtol.q_max = [+1, +1, 1, np.pi]
u \in [-50, +50]^2
                                             pvtol.p nom = pvtol.p
                                             pytol.p std. pytol.tau. pytol.nc = 0.1. 0.02. 4
|\dot{\theta}| \leq 1 and |\theta| \leq \pi
                                                  The user-defined file (part 1)
\tau = 0.02
```

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pvtol.constraints = constraints
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pytol.stage cost = stage cost
pytol.generate cloud = generate cloud
      The user-defined file (part 2)
```

					dev_a	acc =	1				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
1	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
2	2	5	2	2	7.937212e+06	1.243896	0.02	0.04	8	2437.847089	0.250
3	8	7	5	2	1.250875e+06	2.951172	0.02	0.16	18	3401.306977	0.500
4	9	6	7	7	9.170123e+06	8.804688	0.02	0.18	6	3755.852208	0.500
dev_acc = 2											
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	7	17	4	12	8.409123e+06	16.609375	0.02	0.14	5	3210.056159	0.250
1	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
2	9	20	2	19	8.409123e+06	820.515021	0.02	0.18	8	3766.654430	0.250
3	6	17	3	16	6.124112e+06	3.778133	0.02	0.12	5	3284.618189	0.375
4	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
5	9	5	8	4	6.259375e+05	2.951172	0.02	0.18	18	3126.158301	0.500
6	8	12	2	11	7.515030e+04	1.054939	0.02	0.16	17	2891.563097	0.375
7	7	9	5	2	2.442162e+06	15.537363	0.02	0.14	19	3583.879784	0.625
8	9	5	8	6	9.350676e+08	38.215650	0.02	0.18	18	4611.172897	0.625
9	2	12	2	2	8.846257e+06	1.146503	0.02	0.04	7	3408.564392	0.375
10	6	6	6	2	5.282910e+05	1.146503	0.02	0.12	18	3355.846137	0.375
11	9	18	2	13	3.536180e+06	125.875000	0.02	0.18	12	3250.814430	0.125

 $card(\mathcal{A}) = 270 > N_{certification}(\eta = 0.05, \delta = 10^{-3}) = 264$



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7	7	9	5	2	2.442162e+06	15.537363	0.02	0.14	19	3583.879784	0.625
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9	2	12	2	2	8.846257e+06	1.146503	0.02	0.04	7	3408.564392	0.375
10	6	6	6	2	5.282910e+05	1.146503	0.02	0.12	18	3355.846137	0.375
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 $card(A) = 270 > N_{certification}(\eta = 0.05, \delta = 10^{-3}) = 264$

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ρ_f	1	10^{3}
rho_cstr	10^{3}	10^{7}
max_iter	5	20

Small portion of configurations is eligible

5% 13%	dev_acc=1
13%	dev_acc=2

					dev_a	acc =	1				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
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1	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
2	2	5	2	2	7.937212e+06	1.243896	0.02	0.04	8	2437.847089	0.250
3	8	7	5	2	1.250875e+06	2.951172	0.02	0.16	18	3401.306977	0.500
4	9	6	7	7	9.170123e+06	8.804688	0.02	0.18	6	3755.852208	0.500
					dev_a	acc =	2				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	7	17	4	12	8.409123e+06	16.609375	0.02	0.14	5	3210.056159	0.250
1	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.75
2	9	20	2	19	8.409123e+06	820.515021	0.02	0.18	8	3766.654430	0.25
3	6	17	3	16	6.124112e+06	3.778133	0.02	0.12	5	3284.618189	0.375
4	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
5	9	5	8	4	6.259375e+05	2.951172	0.02	0.18	18	3126.158301	0.500
6	8	12	2	11	7.515030e+04	1.054939	0.02	0.16	17	2891.563097	0.375
7	7	9	5	2	2.442162e+06	15.537363	0.02	0.14	19	3583.879784	0.625
8	9	5	8	6	9.350676e+08	38.215650	0.02	0.18	18	4611.172897	0.625
9	2	12	2	2	8.846257e+06	1.146503	0.02	0.04	7	3408.564392	0.375
10	6	6	6	2	5.282910e+05	1.146503	0.02	0.12	18	3355.846137	0.375
11	9	18	2	13	3.536180e+06	125.875000	0.02	0.18	12	3250.814430	0.125

 $card(\mathcal{A}) = 270 > N_{certification}(\eta = 0.05, \delta = 10^{-3}) = 264$

Design parameter	min-value	max-value
N_pred	5	25
κ	1	10
ρ_f	1	10^{3}
rho_cstr	10^{3}	10^{7}
max_iter	5	20

High values of ρ_f lead to unfeasibility

Recall that random sampling of

 $\rho_f \in [1, 1000]$

is applied but only rather small values appear in the resulting admissible settings.

					dev_a	acc =	1				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
1	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
2	2	5	2	2	7.937212e+06	1.243896	0.02	0.04	8	2437.847089	0.250
3	8	7	5	2	1.250875e+06	2.951172	0.02	0.16	18	3401.306977	0.500
4	9	6	7	7	9.170123e+06	8.804688	0.02	0.18	6	3755.852208	0.500
					dev_a	acc =	2				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	7	17	4	12	8.409123e+06	16.609375	0.02	0.14	5	3210.056159	0.250
1	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
2	9	20	2	19	8.409123e+06	820.515021	0.02	0.18	8	3766.654430	0.250
3	6	17	3	16	6.124112e+06	3.778133	0.02	0.12	5	3284.618189	0.375
4	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
5	9	5	8	4	6.259375e+05	2.951172	0.02	0.18	18	3126.158301	0.500
6	8	12	2	11	7.515030e+04	1.054939	0.02	0.16	17	2891.563097	0.375
7	7	9	5	2	2.442162e+06	15.537363	0.02	0.14	19	3583.879784	0.625
8	9	5	8	6	9.350676e+06	38.215650	0.02	0.18	18	4611.172897	0.625
9	2	12	2	2	8.846257e+06	1.146503	0.02	0.04	7	3408.564392	0.375
10	6	6	6	2	5.282910e+05	1.146503	0.02	0.12	18	3355.846137	0.375
11	9	18	2	13	3.536180e+06	125.875000	0.02	0.18	12	3250.814430	0.125

 $card(\mathcal{A}) = 270 > N_{certification}(\eta = 0.05, \delta = 10^{-3}) = 264$

Design parameter	min-value	max-value
N_pred	5	25
κ	1	10
ρ_f	1	10^{3}
rho_cstr	10^{3}	10^{7}
max_iter	5	20

High values of ρ_f lead to unfeasibility

Recall that random sampling of

 $\rho_f \in [1, 1000]$

is applied but only rather small values appear in the resulting admissible settings.

High values of ρ_{cstr} are necessary

Only high values of $\rho_{\rm cstr}$ appear in the admissible settings

					dev_a	acc =	1				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
1	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
2	2	5	2	2	7.937212e+06	1.243896	0.02	0.04	8	2437.847089	0.250
3	8	7	5	2	1.250875e+06	2.951172	0.02	0.16	18	3401.306977	0.500
4	9	6	7	7	9.170123e+06	8.804688	0.02	0.18	6	3755.852208	0.500
dev_acc = 2											
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	7	17	4	12	8.409123e+06	16.609375	0.02	0.14	5	3210.056159	0.250
1	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
2	9	20	2	19	8.409123e+06	820.515021	0.02	0.18	8	3766.654430	0.250
3	6	17	3	16	6.124112e+06	3.778133	0.02	0.12	5	3284.618189	0.375
4	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
5	9	5	8	4	6.259375e+05	2.951172	0.02	0.18	18	3126.158301	0.500
6	8	12	2	11	7.515030e+04	1.054939	0.02	0.16	17	2891.563097	0.375
7	7	9	5	2	2.442162e+06	15.537363	0.02	0.14	19	3583.879784	0.625
8	9	5	8	6	9.350676e+08	38.215650	0.02	0.18	18	4611.172897	0.625
9	2	12	2	2	8.846257e+06	1.146503	0.02	0.04	7	3408.564392	0.375
10	6	6	6	2	5.282910e+05	1.146503	0.02	0.12	18	3355.846137	0.375
11	9	18	2	13	3.536180e+06	125.875000	0.02	0.18	12	3250.814430	0.125
12	6	19	2	2	7.430228e+06	2.951172	0.02	0.12	14	3360.845813	0.125

 $card(\mathcal{A}) = 270 > N_{certification}(\eta = 0.05, \delta = 10^{-3}) = 264$

Design parameter	min-value	max-value
N_pred	5	25
κ	1	10
ρ_f	1	10^{3}
rho_cstr	10^{3}	10^{7}
max_iter	5	20

High values of ρ_f lead to unfeasibility

Recall that random sampling of

 $\rho_f \in [1, 1000]$

is applied but only rather small values appear in the resulting admissible settings.

High values of ρ_{cstr} are necessary

Only high values of $\rho_{\rm cstr}$ appear in the admissible settings

⇒ The scenarios are constraints-challenging

					dev_a	acc =	1				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
1	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
2	2	5	2	2	7.937212e+06	1.243896	0.02	0.04	8	2437.847089	0.250
3	8	7	5	2	1.250875e+06	2.951172	0.02	0.16	18	3401.306977	0.500
4	9	6	7	7	9.170123e+06	8.804688	0.02	0.18	6	3755.852208	0.500
					dev_a	acc =	2				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	7	17	4	12	8.409123e+06	16.609375	0.02	0.14	5	3210.056159	0.250
1	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
2	9	20	2	19	8.409123e+06	820.515021	0.02	0.18	8	3766.654430	0.250
3	6	17	3	16	6.124112e+06	3.778133	0.02	0.12	5	3284.618189	0.375
4	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
5	9	5	8	4	6.259375e+05	2.951172	0.02	0.18	18	3126.158301	0.500
6	8	12	2	11	7.515030e+04	1.054939	0.02	0.16	17	2891.563097	0.375
7	7	9	5	2	2.442162e+06	15.537363	0.02	0.14	19	3583.879784	0.625
8	9	5	8	6	9.350676e+06	38.215650	0.02	0.18	18	4611.172897	0.625
9	2	12	2	2	8.846257e+06	1.146503	0.02	0.04	7	3408.564392	0.375
10	6	6	6	2	5.282910e+05	1.146503	0.02	0.12	18	3355.846137	0.375
11	9	18	2	13	3.536180e+06	125.875000	0.02	0.18	12	3250.814430	0.125
										3360.845813	

 $card(\mathcal{A}) = 270 > N_{certification}(\eta = 0.05, \delta = 10^{-3}) = 264$

Design parameter	min-value	max-value
N_pred	5	25
κ	1	10
ρ_f	1	10^{3}
rho_cstr	10^{3}	10^{7}
max_iter	5	20

Impact of dev_acc

Increasing dev_acc increases the number of eligible configurations!

					dev_a	acc =	1				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
1	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
2	2	5	2	2	7.937212e+06	1.243896	0.02	0.04	8	2437.847089	0.250
3	8	7	5	2	1.250875e+06	2.951172	0.02	0.16	18	3401.306977	0.500
4	9	6	7	7	9.170123e+06	8.804688	0.02	0.18	6	3755.852208	0.500
					dev_a	acc =	2				
	kappa	N_pred	n_steps	n_ctr	rho_cstr	rho_final	tau	tau_u	max_iter	cost	alpha
0	7	17	4	12	8.409123e+06	16.609375	0.02	0.14	5	3210.056159	0.250
1	9	7	3	8	9.646822e+06	178.800537	0.02	0.18	11	7859.487689	0.750
2	9	20	2	19	8.409123e+06	820.515021	0.02	0.18	8	3766.654430	0.250
3	6	17	3	16	6.124112e+06	3.778133	0.02	0.12	5	3284.618189	0.375
4	4	6	2	4	9.102911e+06	24.259781	0.02	0.08	16	4404.438416	0.625
5	9	5	8	4	6.259375e+05	2.951172	0.02	0.18	18	3126.158301	0.500
6	8	12	2	11	7.515030e+04	1.054939	0.02	0.16	17	2891.563097	0.375
7	7	9	5	2	2.442162e+06	15.537363	0.02	0.14	19	3583.879784	0.625
8	9	5	8	6	9.350676e+06	38.215650	0.02	0.18	18	4611.172897	0.625
9	2	12	2	2	8.846257e+06	1.146503	0.02	0.04	7	3408.564392	0.375
10	6	6	6	2	5.282910e+05	1.146503	0.02	0.12	18	3355.846137	0.375
11	9	18	2	13	3.536180e+06	125.875000	0.02	0.18	12	3250.814430	0.125
			2		7.430228e+06					3360.845813	0.125

 $card(A) = 270 > N_{certification}(\eta = 0.05, \delta = 10^{-3}) = 264$

Design parameter	min-value	max-value
N_pred	5	25
κ	1	10
ρ_f	1	10^{3}
rho_cstr	10^{3}	10^{7}
max_iter	5	20

Impact of dev_acc

Increasing dev_acc increases the number of eligible configurations!

Large eligible possibilities of prediction horizons

$N_{\rm pred} \in [0.2, 1.26]$	dev_acc=1
$N_{\rm pred} \in [0.48, 3.24]$	dev_acc=2

Conclusion and future extensions

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✓ Design of NMPC setting: A Relevant problem!

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✓ Design of NMPC setting: A Relevant problem!

Any of the discarded settings can be an intuitive choice of someone!

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optimal control problems of the following form (soft constraints are a saturations):			
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- ✓ Design of NMPC setting: A Relevant problem! Any of the discarded settings can be an intuitive choice of someone!
- ✓ The freely available MPC_tuner is a first step! Any comment or suggestion is more than welcome!
- ✓ Extension 1: Include fast-gradient option.
- ✓ Extension 2: Include other solvers inside CasADi The current implementation uses exclusively IPOPT
- ✓ Extension 3: Include time varying weighting and penalties on the state excursion.
- ✓ **Extension 4**: Accelerate the heuristic using ML!

Each example needed \approx 1hr under MacBook Pro,2.4GHz intel Corei9

