Tango steps in a moving-horizon cabaret

Theory, concepts, heuristics and examples ...

Mazen Alamir

CNRS - University of Grenoble-Alpes

Outline

1. Non conventional NMPC Formulations
   - Economic MPC
   - Bringing the infinity closer
2. GPU-related topics
   - Some experiments
   - Use-case
3. Machine Learning-related topics
   - Stochastic NMPC by supervised clustering
   - ML-Model-based monitoring control updating period in NMPC
4. Discussion: Threats & suggestions for a data-dominated future

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2 GPU-related topics

3 Machine Learning-related topics

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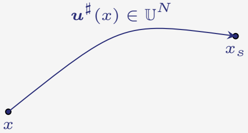

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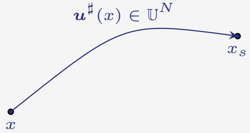

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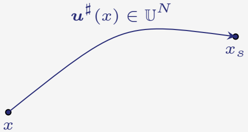

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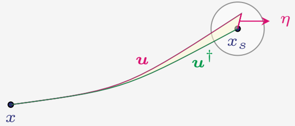

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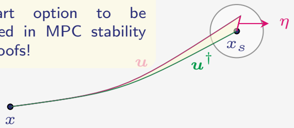

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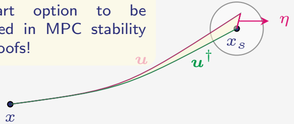

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A trajectory $(\boldsymbol{x},\boldsymbol{u})$ is said to be ϵ-quasi steady optimal if and only if the following conditions hold for all k:

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Proposition. For any desired $\epsilon > 0$, $\exists$ **sufficiently high** α, γ s.t the resulting closed-loop trajectory starting at $x_0 \in \mathbb{X}_0$ is asymptotically ϵ-quasi steady optimal.

Moreover, for dynamics that are obtained by time sampling, the size of the terminal region might be further reduced by reducing the sampling period τ.

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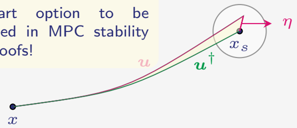

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Bringing infinity closer!

MPC with exponentially increasing weight

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M.A Stability proof for nonlinear MPC design using monotonically increasing weighting ..., **Automatica 87**, 2018.
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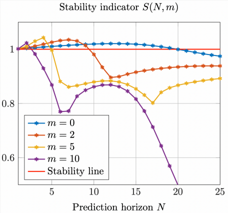

Evolution of the highest module of closed-loop eigenvalues $S(N, m)$

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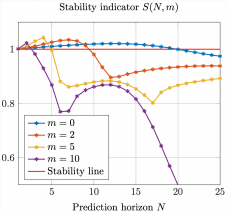

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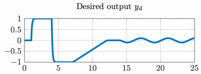

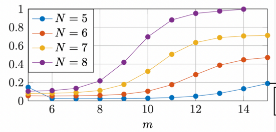

$$\frac{\Big[\sum_i \ell_i^{cl}\Big]^{\text{Proposed}}}{\Big[\sum_i \ell_i^{cl}\Big]^{\text{term. constr.}}}$$

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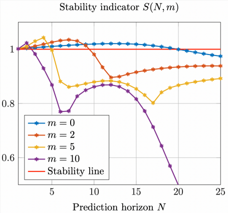
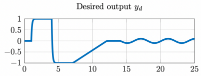
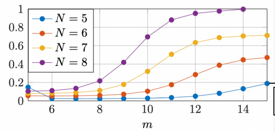


Evolution of the highest module of closed-loop eigenvalues $S(N, m)$





$$\frac{\left[\sum_i \ell_i^{cl}\right]^{\text{Proposed}}}{\left[\sum_i \ell_i^{cl}\right]^{\text{term. constr.}}}$$

The shorter N, the stronger is the advantage!

M.A Stability proof for nonlinear MPC design using monotonically increasing weighting . . . , **Automatica 87**, 2018.
M.A Numerical investigation regarding . . . Application to the control of real-life cryogenic plant, **NMPC workshop** 2018.

Bringing infinity closer!

MPC with exponentially increasing weight

Cost function

$$J(\boldsymbol{u}, x) := \sum_{k=1}^{N} [k/N]^m \Big[\varphi_m \ell_k^{\boldsymbol{u}} + (1-\varphi_m) V_k^{\boldsymbol{u}}\Big]$$

- ℓ is the stage cost of interest
- V is a **local** controlled Lyapunov function
- $\varphi(0) = 1$ and $\lim_{m\to\infty} \varphi_m = 0$
- **Assumption**: N-reachability over $\mathbb{X}_0$

Proposition. For sufficiently high m $\rightarrow$ Closed-loop stability of for any initial state inside $\mathbb{X}_0$.

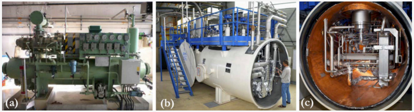
Questions

Q1. Are we still minimizing the same cost?

Q2. Implication on the computation time!

Q1-Q2

Cryogenic station of CEA-INAC-SBT



$$x^+ = Ax + Bu + Gw$$
$$y = Cx + Du \quad (x, u, y, w) \in \mathbb{R}^{24} \times \mathbb{R}^3 \times \mathbb{R}^3 \times \mathbb{R}$$

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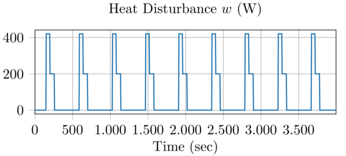

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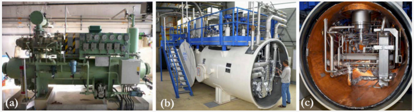

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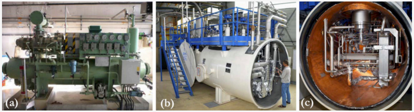

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$$\varepsilon_f \|x_N\|^2 + \sum_{k=1}^{N} [k/N]^m \left[\|y_i\|^2_{Q_y} + \varepsilon\|x_i\|^2\right]$$

Controller Settings	ϵ_f	m	ϵ	N
Proposed Controller	0	3	0.01	10
Controller 1	0	0	0.01	10
Controller 2	100	0	0.01	10

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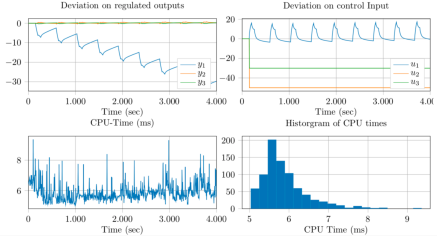
Q1-Q2 **Controller 1**



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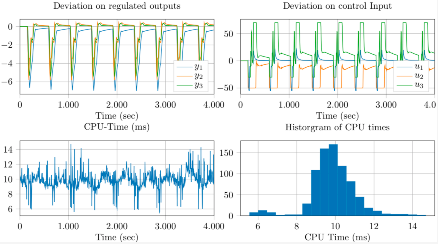
Q2. Implication on the computation time!

Q1-Q2 **Controller 2**



$$\varepsilon_f \|x_N\|^2 + \sum_{k=1}^{N} [k/N]^m \Big[\|y_i\|^2_{Q_y} + \varepsilon \|x_i\|^2\Big]$$

Controller Settings	ϵ_f	m	ϵ	N
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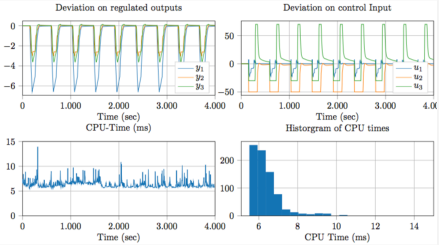
Q1-Q2 **Proposed**



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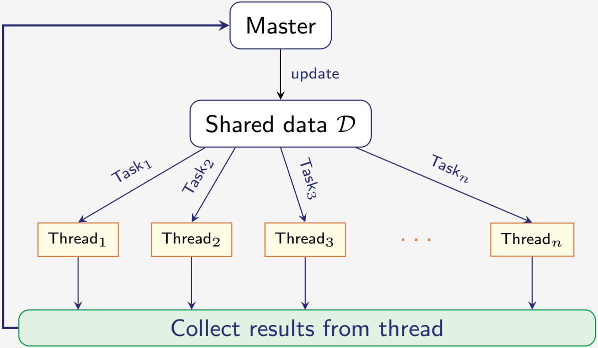
Distributing the computation

GPU, FPGA ...



$n \to 10^7$

Distributing the computation

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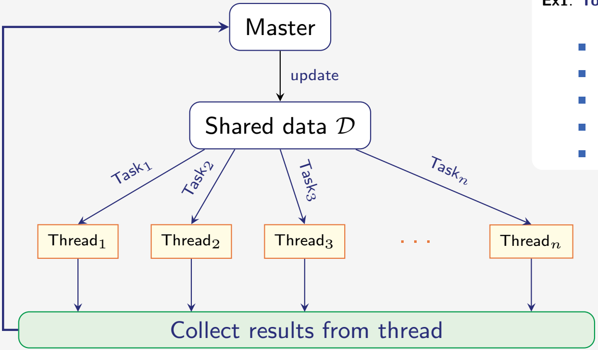


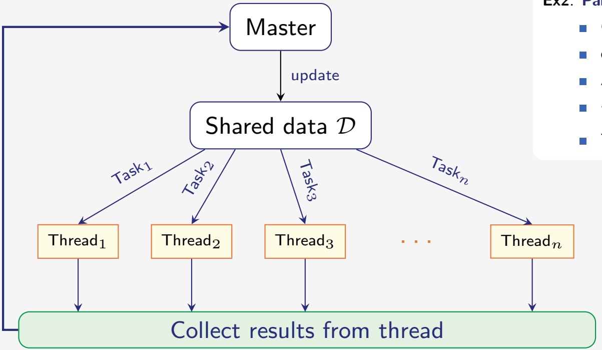
$n \to 10^7$

Ex1. Toy example on Google-Colab

- $2D$ discrete time dynamics
- simulate $N = 20$ steps
- for ≈ 500000 initial states
- time CPU $\approx$ 2 min.
- **GPU-time $\approx$ 400 μ-sec**

Distributing the computation

GPU, FPGA ...



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Ex2. Parametrized stochastic MPC

- Cost function $J(p \mid w)$
- quantized sets of values $\mathbb{P}$
- A set of realizations $\mathbb{W}$
- $n :=$ card$(\mathbb{P}) \cdot$ card$(\mathbb{W})$
- Task$_{ij} \leftarrow J(p^{(i)} \mid w^{(j)})$

Distributing the computation

GPU, FPGA ...

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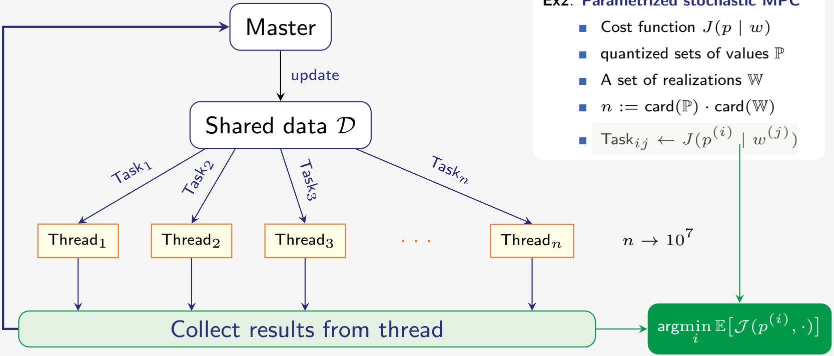
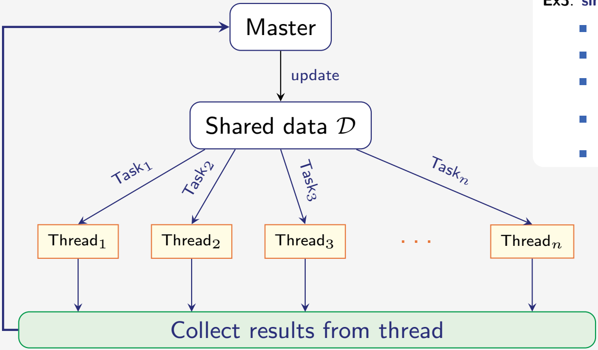


DISTRIBUTING THE COMPUTATION

GPU, FPGA ...



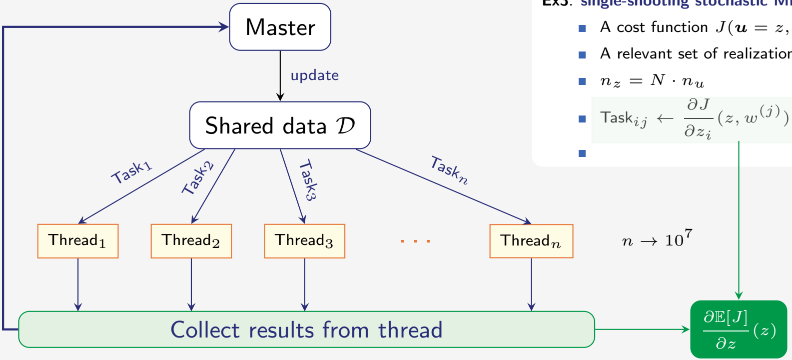
Ex3. single-shooting stochastic MPC

- A cost function $J(\boldsymbol{u} = z, w)$
- A relevant set of realizations $\mathbb{W}$
- $n_z = N \cdot n_u$
- $\text{Task}_{ij} \leftarrow \dfrac{\partial J}{\partial z_i}(z, w^{(j)})$
-

$n \to 10^7$

Distributing the computation

GPU, FPGA ...



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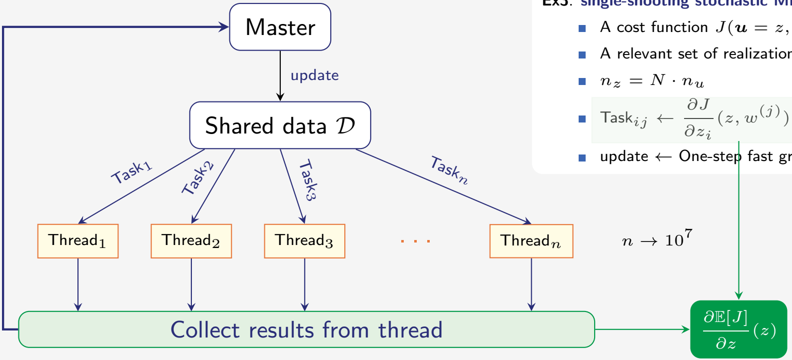
- update $\leftarrow$ One-step fast gradient!



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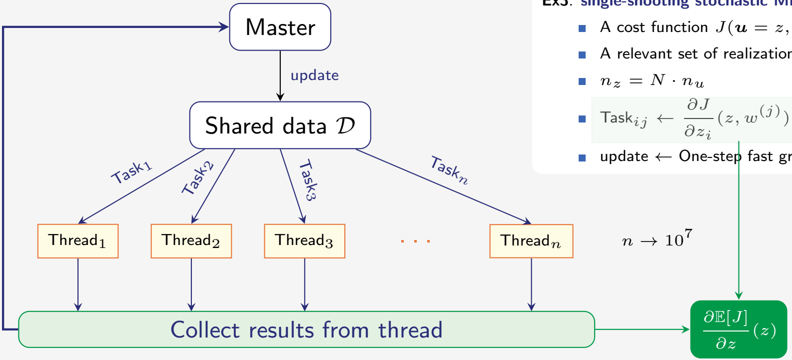


https://colab.research.google.com/drive/1CJl4IaQ1s23D5Wn_6P-uIIzIgEfsr5ji?usp=sharing

```
Number of scenarios = 20000
Prediction Horizon = 20
gpu computation time = 0.0002663135528564453
Number of individual tasks = 800000
```

```
t1 = time.time()

Grad(x0_gpu, U_gpu, W_gpu, J_gpu, G_gpu, mode_gpu,
     grid=(256, 16, 1), block=(256, 1, 1))
t2 = time.time()
```

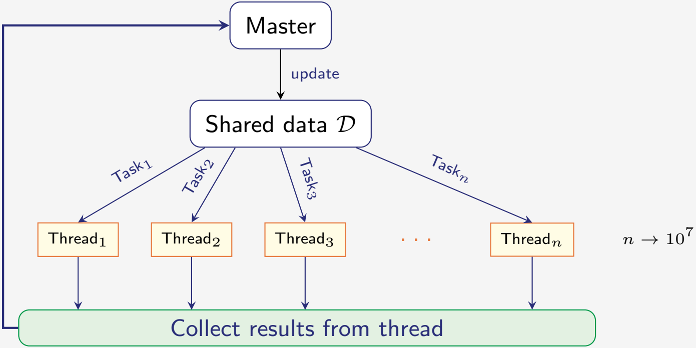
Combined therapy

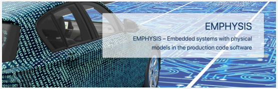
$n_x = 4, n_w = 13$

$n_u = 2, N = 20$

Distributing the computation

GPU, FPGA . . .

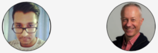




GPU-Based NMPC of a semi-active suspension

Distributing the computation

GPU-Based MPC of a semi-active suspension.



K. M. M. Rathai O. Sename

Half-Car SA-suspension

$$m_s \ddot{z}_s = -F_{s,\ell}(sa_\ell) - F_{s,r}(sa_r)$$

$$I_x \ddot{\theta} = \ell_\ell F_{s,\ell}(sa_\ell) - \ell_r F_{s,r}(sa_r)$$

$$m_{us,\ell} \ddot{z}_{us,\ell} = F_{t,\ell} - F_{s,\ell}(sa_\ell)$$

$$m_{us,r} \ddot{z}_{us,r} = F_{t,r} - F_{s,r}(sa_r)$$

(ℓ) left, (r) right, (s) chassis, (t) wheel

$$F_{s,i} = -k_{s,i}(z_{s,i}(\theta) - z_{us,i}) + sa_i$$

$$F_{t,i} = -k_{t,i}(z_{us,i} - z_{r,i}) \quad i \in \{\ell, r\}$$

Road profile ↲

K. M. M. Rathai et al., GPU-based parametrized NMPC scheme . . . IEEE Control Systems Letters, Vol. 3, Number 3, 2019

Distributing the computation

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Road profile

$$sa_i = k_0 z_{d,i} + c_0\dot{z}_{d,i} + f_c\phi_i \tanh(a_1\dot{z}_{d,i} + a_2 z_{d,i})$$

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Control objective

- Comfort ($\downarrow |\ddot{z}_s|$)
- Ride handling ($\downarrow |\ddot{\theta}^2|$)
- Box constraints on x/u

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- Ride handling $(\downarrow |\ddot{\theta}^2|)$
- Box constraints on x/u

Manipulated variables

- $u := (\phi_\ell, \phi_r) \in \mathbb{E}^2 \subset \mathbb{R}^2$
- $\mathbb{E}$ is a quantized (discrete) set.

K. M. M. Rathai et al., GPU-based parametrized NMPC scheme . . . IEEE Control Systems Letters, Vol. 3, Number 3, 2019

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Control objective

- Comfort $(\downarrow |\ddot{z}_s|)$
- Ride handling $(\downarrow |\ddot{\theta}^2|)$
- Box constraints on x/u

Manipulated variables

- $u := (\phi_\ell, \phi_r) \in \mathbb{E}^2 \subset \mathbb{R}^2$
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$\dot{x} = f(x, u, w)$, $(x, u, w) \in \mathbb{R}^8 \times \mathbb{R}^2 \times \mathbb{R}^2$, $\tau_s \leq$ 5msec

K. M. M. Rathai et al., GPU-based parametrized NMPC scheme ... IEEE Control Systems Letters, Vol. 3, Number 3, 2019

Distributing the computation

GPU-Based MPC of a semi-active suspension.


K. M. M. Rathai


O. Sename

Half-Car SA-suspension

$$m_s\ddot{z}_s = -F_{s,\ell}(sa_\ell) - F_{s,r}(sa_r)$$
$$I_x\ddot{\theta} = \ell_\ell F_{s,\ell}(sa_\ell) - \ell_r F_{s,r}(sa_r)$$
$$m_{us,\ell}\ddot{z}_{us,\ell} = F_{t,\ell} - F_{s,\ell}(sa_\ell)$$
$$m_{us,r}\ddot{z}_{us,r} = F_{t,r} - F_{s,r}(sa_r)$$

(ℓ) left, (r) right, (s) chassis, (t) wheel

$$F_{s,i} = -k_{s,i}(z_{s,i}(\theta) - z_{us,i}) + sa_i$$
$$F_{t,i} = -k_{t,i}(z_{us,i} - z_{r,i}) \quad i \in \{\ell, r\}$$

Road profile

$$sa_i = k_0 z_{d,i} + c_0\dot{z}_{d,i} + f_c\phi_i \tanh(a_1\dot{z}_{d,i} + a_2 z_{d,i})$$

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State of the art general NLP solver

- ACADO-qpOases / multiple shooting
- Symbolic automatic differentiation
- 4-th order Runge-Kutta integrator
- Code-generation based
- Standard p.w.c control profile
- projection of the quantized set
- Monitor the # iterations N_s

Matlab/simulink, Intel Core i7 PC

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GPU/Simulation based solver

- Constant profile
- $\text{Card}(\mathbb{E})^2$ possibilities
- **Each** is simulated by a single thread
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  Take the cost minimizer
- **otherwise**:

  Minimize the constraint violation

NVIDIA GTX 1050 / 768 CUDA cores

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(FA) Feasibility
(CT) Computation Time
(NCLO) Normalized Closed-Loop Objective
(N_s) number of Newton iterations
(n_ϕ) card($\mathbb{E}$)

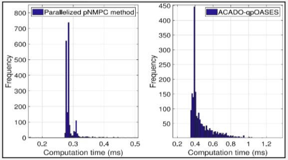
TABLE I
ACADO-qpOASES NMPC Controller

N_s	FA	Mean CT (ms)	Max CT (ms)	NCLO
5	✗	0.70	1.6	—
10	✗	0.95	2.2	—
15	✓	1.3	2.9	0.6484
20	✓	1.5	3.0	0.6412
25	✓	1.9	3.9	0.6317

TABLE II
Parallelized pNMPC Method

$\{n_{\phi_l}, n_{\phi_r}\}$	FA	Mean CT (ms)	Max CT (ms)	NCLO
{2, 2}	✓	0.35	0.62	0.4679
{4, 4}	✓	0.35	0.60	0.4640
{8, 8}	✓	0.35	0.61	0.4646
{16, 16}	✓	0.36	0.55	0.4588
{32, 32}	✓	0.41	0.67	0.4568

(Courtesy K. M. M. Rathai)



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Stochastic MPC using supervised clustering

Distributing the data building over the real-life time

Dynamics	$\dot{x} = f(x, u, w)$
Cost	$J(\boldsymbol{u}\vert(x, w))$
Constraints	$g(\boldsymbol{u}\vert(x, w))$
w**-statistics**	$\mathcal{W}$

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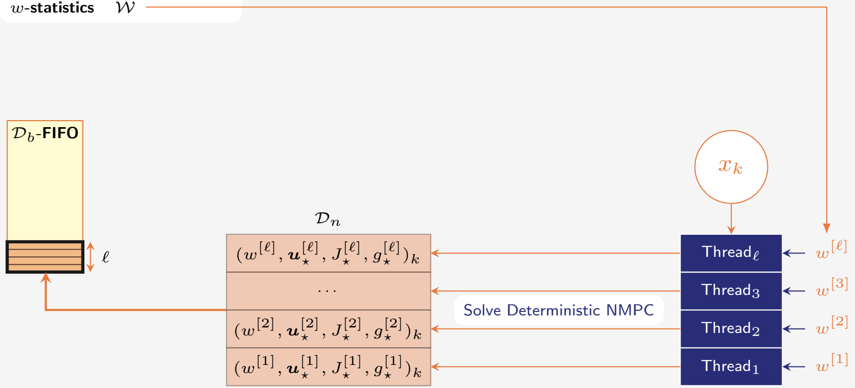

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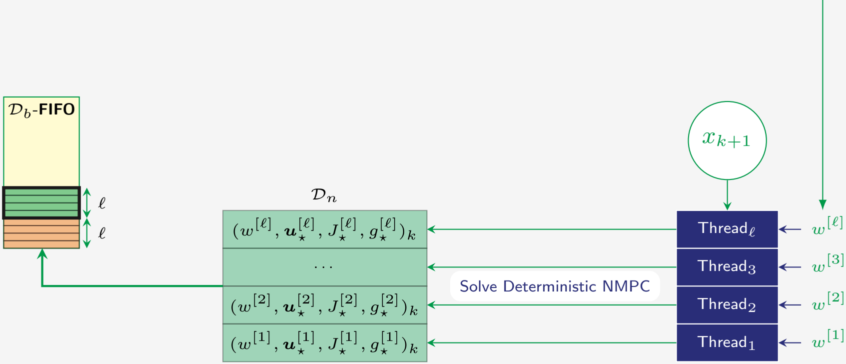

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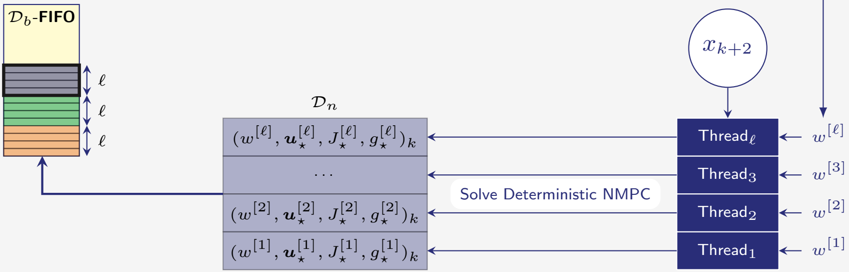

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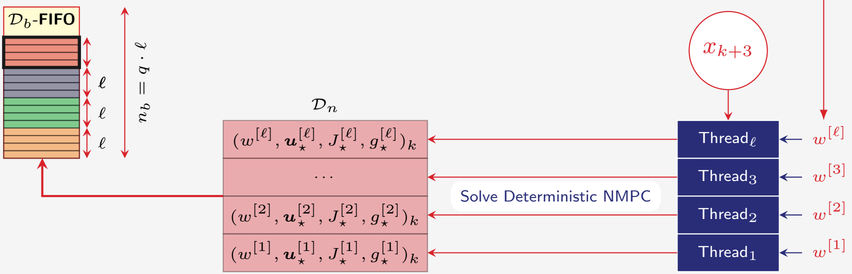

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STOCHASTIC MPC USING SUPERVISED CLUSTERING

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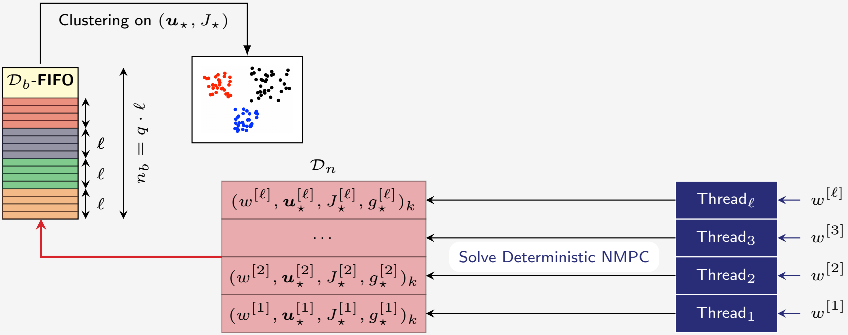

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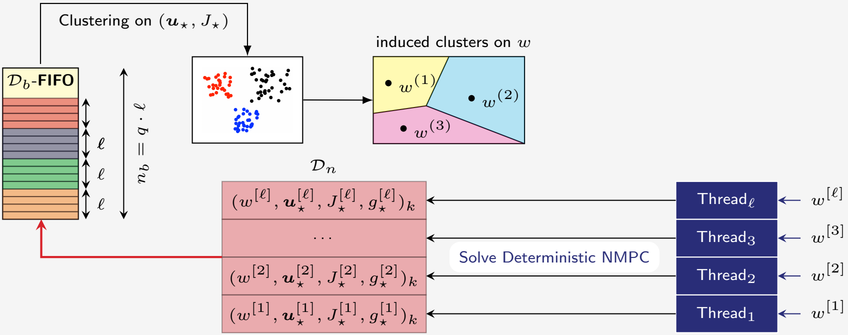

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under

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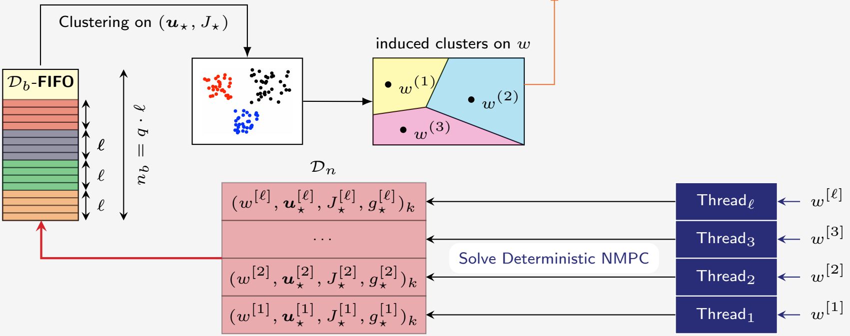

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x_1 tumor cell population;
x_2 circulating lymphocytes population;
x_3 chemotherapy drug concentration;
x_4 effector immune cell population;
u_1 rate of introduction of immunotherapy drug;
u_2 rate of introduction of chemotherapy drug.

and the dynamics is given by

$$\dot{x}_1 = ax_1(1 - bx_1) - c_1x_4x_1 - k_3x_3x_1$$
$$\dot{x}_2 = -\delta x_2 - k_2x_3x_2 + s_2$$
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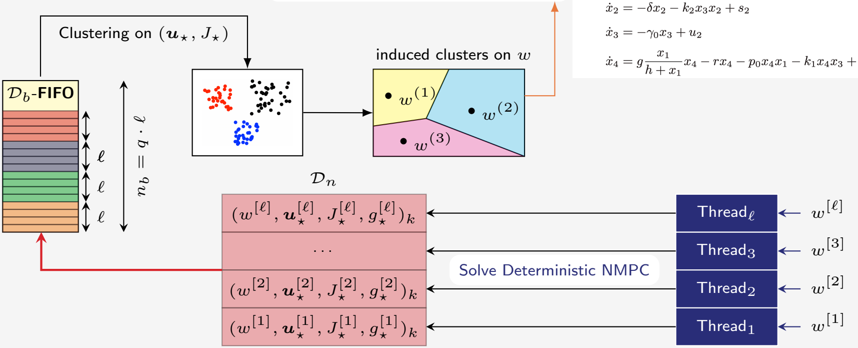

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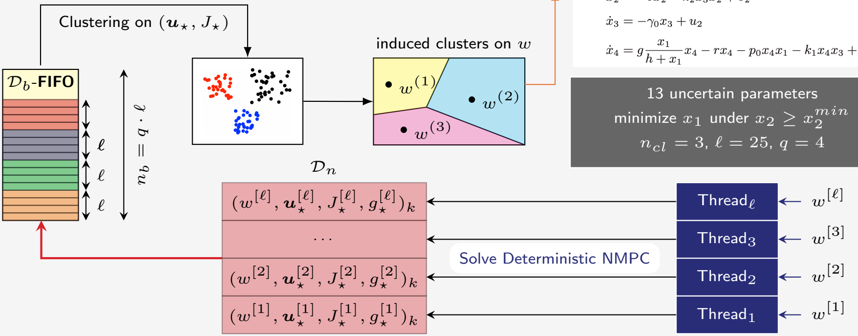
13 uncertain parameters
minimize x_1 under $x_2 \geq x_2^{min}$
$n_{cl} = 3$, $\ell = 25$, $q = 4$



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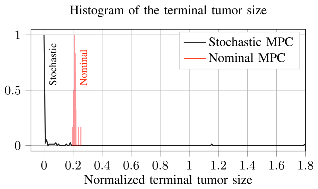

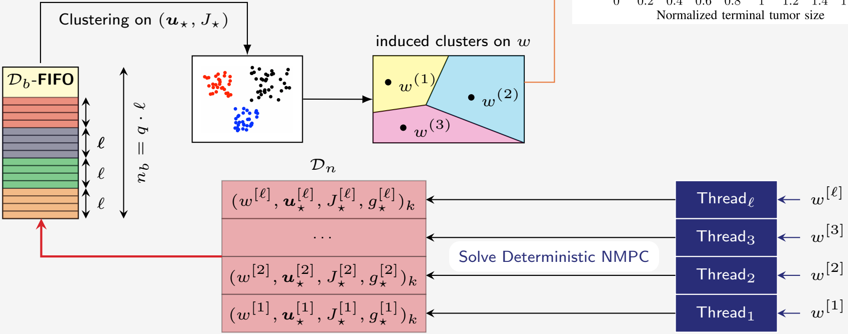

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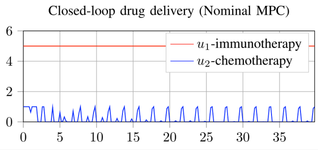

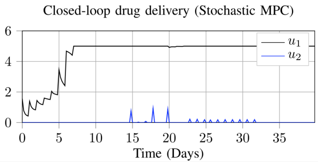

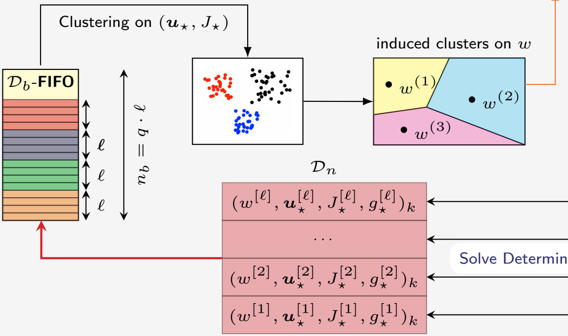

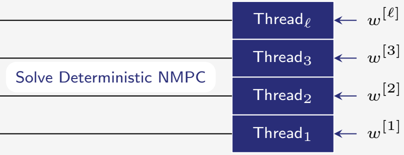

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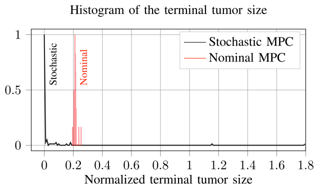
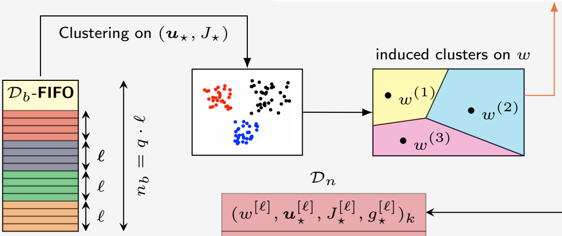
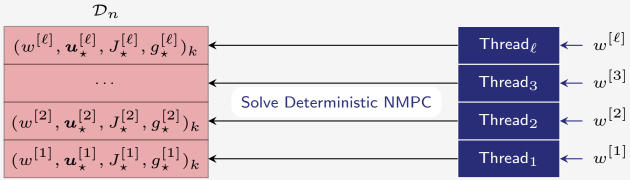


Statistics of the Computation Times (in ms) of a Single Solution of the Optimization Problem. (CasADi [4] (Python Version) on a MacBookPro 2.9 GHz Intel Core i7)

	Mean (ms)	**Standard deviation** (ms)
Nominal	270	76
Stochastic	383	330





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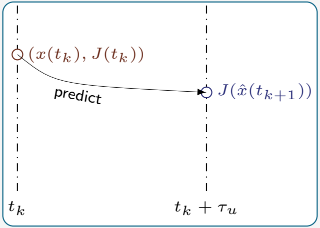
Monitoring Control Updating Period

New ML-induced opportunities (preliminary)



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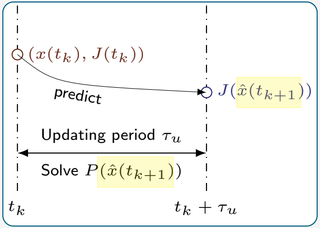

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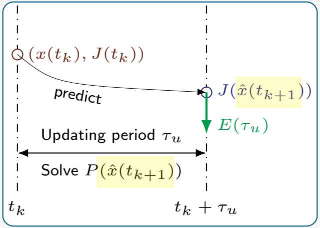

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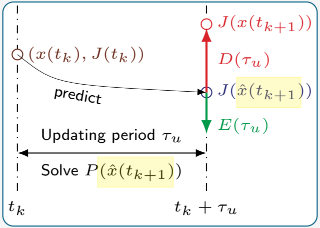

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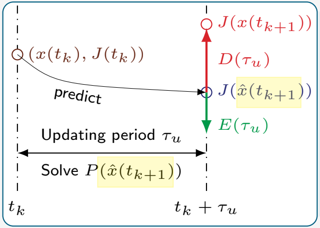

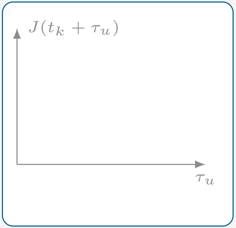

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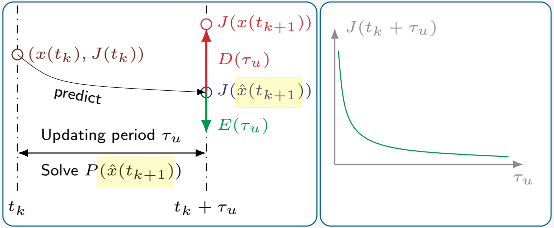

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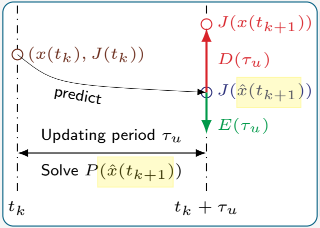

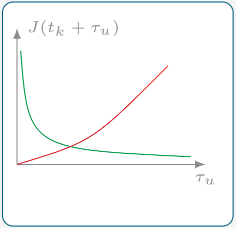

Monitoring Control Updating Period

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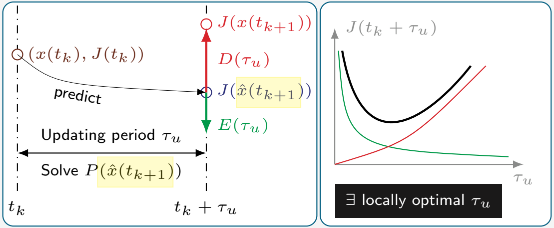

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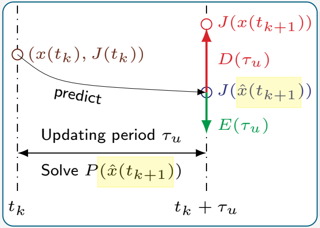

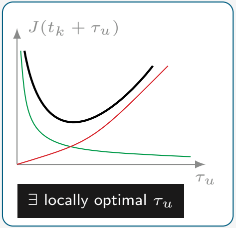

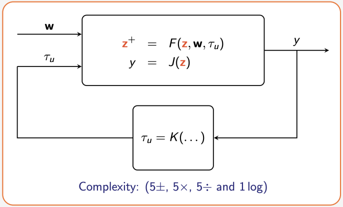

M.A. Monitoring Control Updating Period In Fast Gradient-Based NMPC. ECC2013, 2013

Monitoring Control Updating Period

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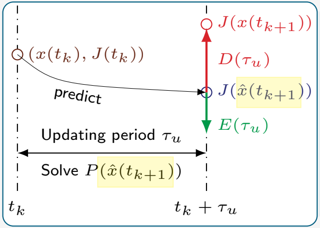

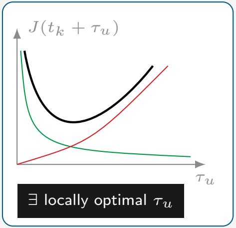

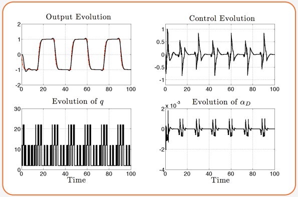

$\tau_u := q \times$ cpu of a single iteration

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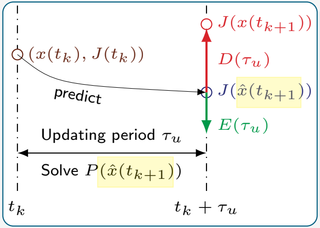

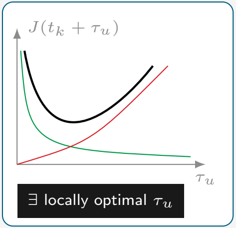

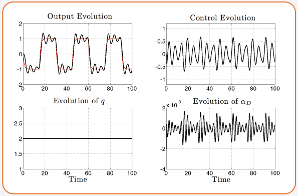

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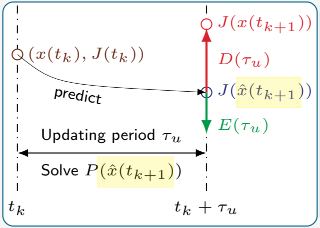

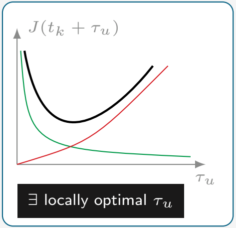

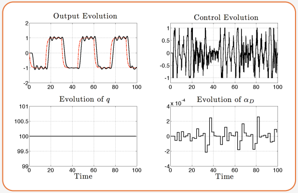

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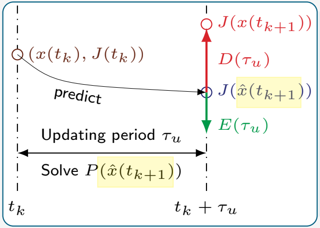

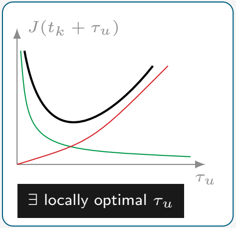

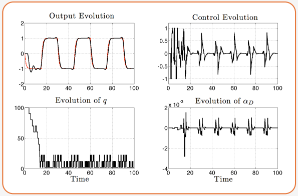

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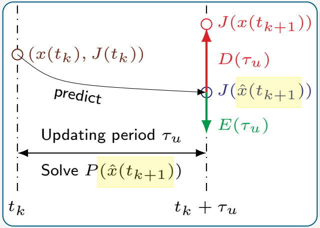

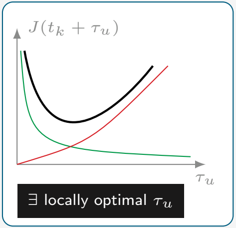

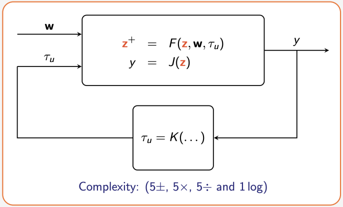

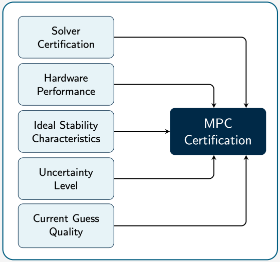

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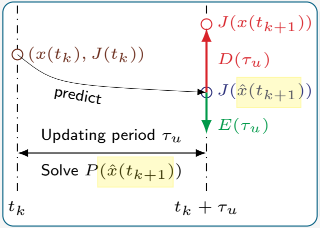
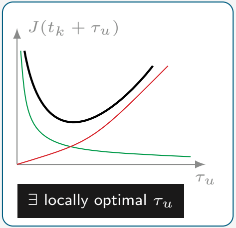
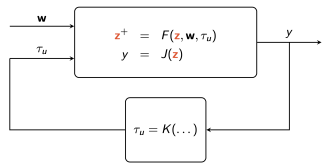
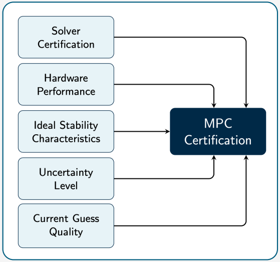
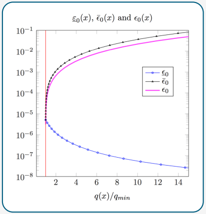






Complexity: (5±, 5×, 5÷ and 1 log)





ϵ_0: required precision

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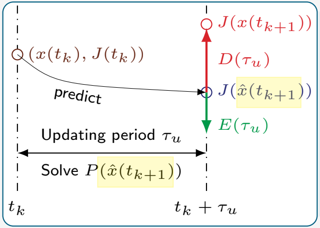
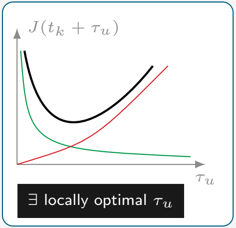
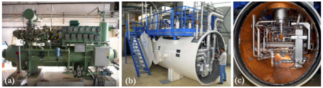
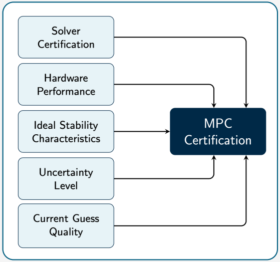
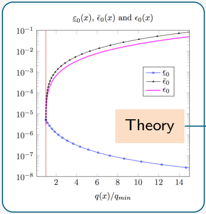






Simulate CL-NMPC
Fast Gradient
Warm start
Random (τ_u, w)





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Monitoring Control Updating Period

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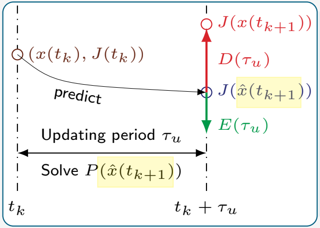
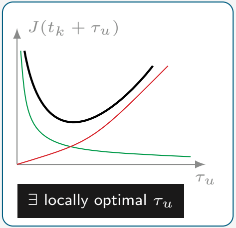
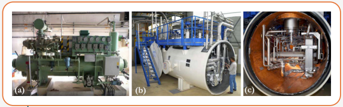




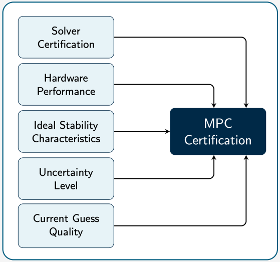


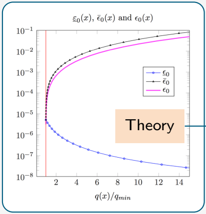
- Simulate CL-NMPC
- Fast Gradient
- Warm start
- Random (τ_u, w)

Learning data:

$$X = (J, \tau_u, w)$$

$$y = \frac{J^+}{J+1}$$





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Monitoring Control Updating Period

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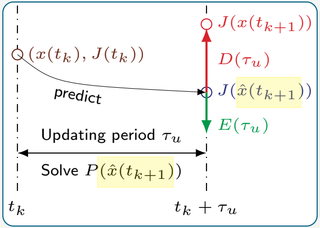

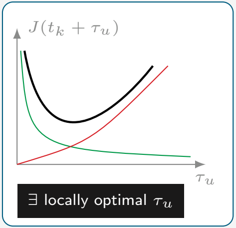

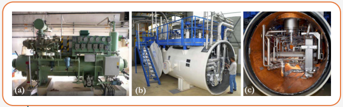

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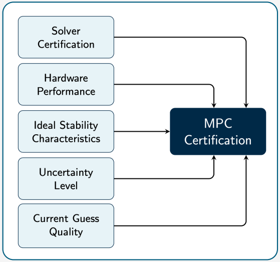

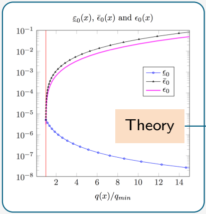

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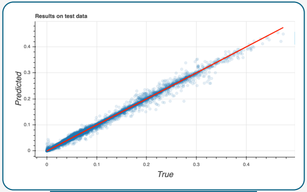

$J^+ = \text{ML}(J(x), \tau_u, w)$

ϵ_0: required precision

$q(x) \leftarrow$ stage cost

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Monitoring Control Updating Period

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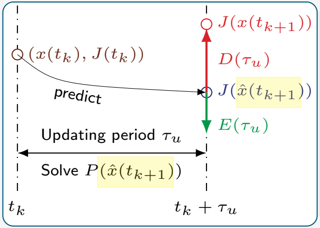

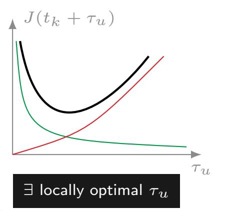

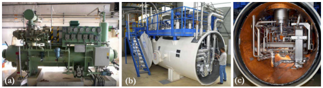

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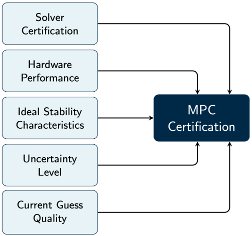

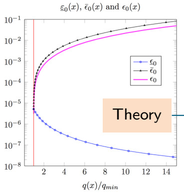

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$q(x) \leftarrow$ stage cost

check

$$J(t_{k+1}) = \textbf{ML}(J(t_k), \tau_u, w)$$

$$t_{k+1} = t_k + \tau_u$$

$$\min_{\tau_u(\cdot)} \mathbb{E}(J(T_P)) \text{ s.t. } \begin{cases} \tau_u^{(i)} > 0 \\ \sum_i \tau_u^{(i)} = T_p \end{cases}$$

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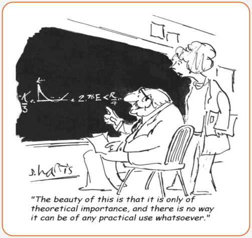
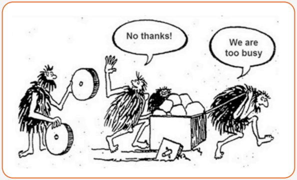
Conclusion



Control



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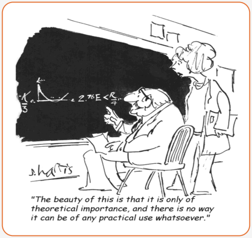
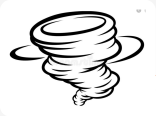
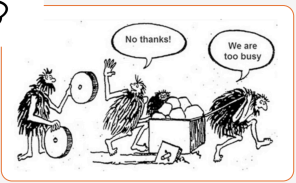


Control

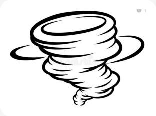
Machine Learning

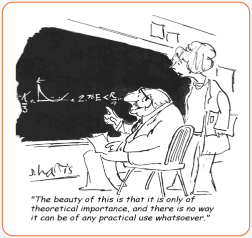




Conclusion

Machine Learning





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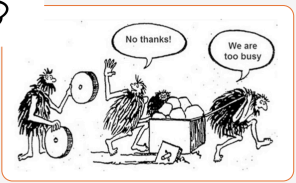
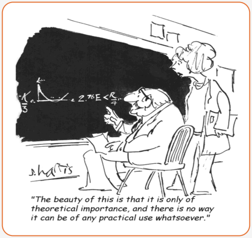


Computational technologies

GPU, FPGA, Containers, . . .

Conclusion



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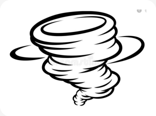
Machine Learning



AI-Autonomous X

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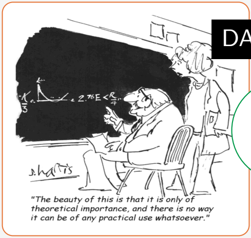
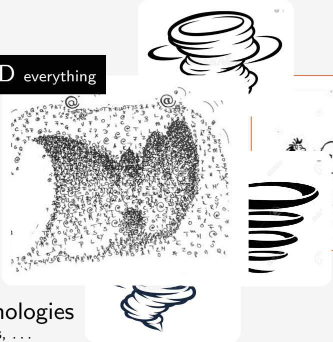
Conclusion

Machine Learning



DATA-BASED everything

Control



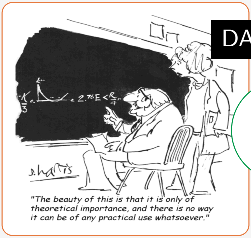
AI-Autonomous X

Computational technologies
GPU, FPGA, Containers, ...

Conclusion

Business as usual is not an option!

Machine Learning



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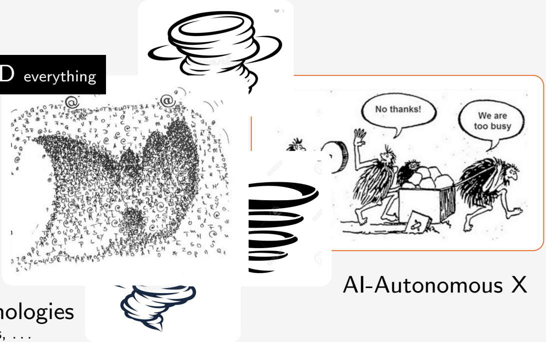

AI-Autonomous X

Computational technologies
GPU, FPGA, Containers, . . .

Threat: Recycling old recipes . . .

Finding a solution to a real-life problem with provable qualities

$\neq$

Exhibiting sufficient conditions for such a solution to exist.

Threat: Recycling old recipes . . .

Finding a solution to a real-life problem with provable qualities	$\neq$	Exhibiting sufficient conditions for such a solution to exist.

- Once such **conditional** claims are published . . .
- Nobody recalls the **unrealistic** supporting assumptions
- The absence of proofs is opposed to excellent heuristics that would efficiently solve **infinitely wider class** of real-life problems
- This was already nuisible in the past
- It is even more today as other actors (including giants) are working towards efficient and generic solutions

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Keep critical and focus on the right fights!

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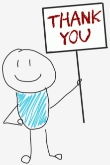
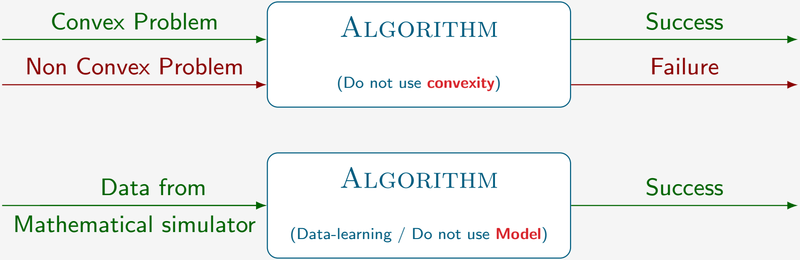


Conjecture


Convex Problem
Non Convex Problem
Algorithm
(Do not use convexity)
Success
Failure

Conjecture



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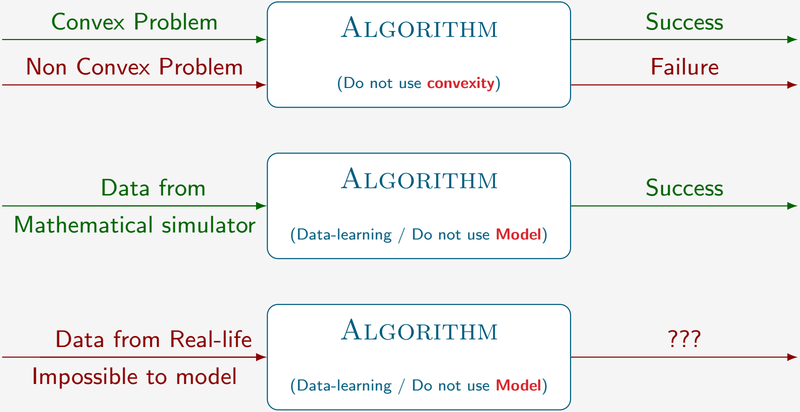
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Impossible to model
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???

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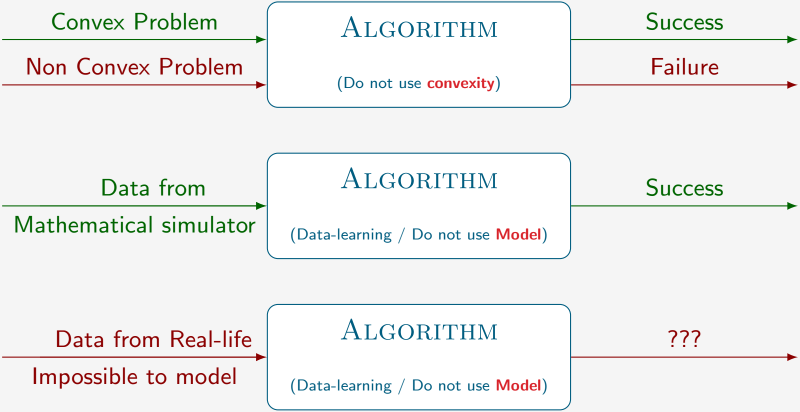

What if (Success) $\Leftrightarrow$ ($\exists$ model)?