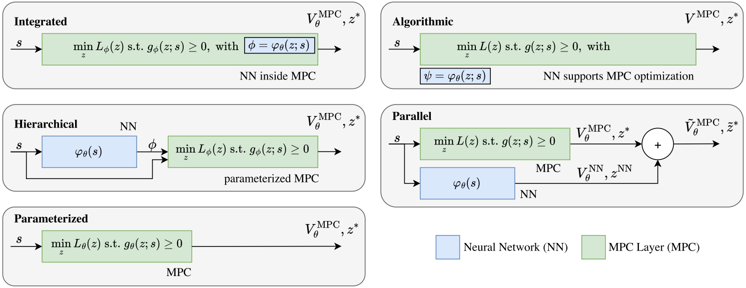
# Differentiable NMPC with acados

Katrin Baumgärtner

University of Freiburg

Predict, Control, Learn: Combining Model Predictive Control and Reinforcement Learning
Tutorial Session at ECC 2026, Reykjavík, July 2026

# Motivation




**Building blocks for practical implementations.**

- Efficient numerical solvers for optimal control problems.
- Availability of solution sensitivities with respect to problem parameters.

# Tutorial Roadmap

| | *Talk* | *Presenter* | *Duration* |
|---|---|---|---|
| ✓ | Markov Decision Processes – a unifying perspective on MPC and RL | Jasper Hoffmann | 20min |
| ✓ | Synthesis of Model Predictive Control and Reinforcement Learning | Rudolf Reiter | 30min |
| ✓ | Reinforcement Learning over MPC: Why does it work? | Dirk Reinhardt | 30min |
| ➤ | **Differentiable NMPC with `acados`** | **Katrin Baumgärtner** | **20min** |
| | MPCRL with `leap-c` | Jasper Hoffmann | 20min |

At the end of each talk there will be time for questions!

Tutorial webpage for slides and more!

# Reminder: Parameterized OCP

## Parameterized OCP with parameters $\phi$.

**OCP-structured NLP.**

$$
\begin{aligned}
\min_{\substack{x_0,\dots,x_N,\\ u_0,\dots,u_{N-1}}} \quad & \bar{V}_\phi^{\mathrm{MPC}}(x_N) + \sum_{k=0}^{N-1} l_\phi^{\mathrm{MPC}}(x_k, u_k) \\
\text{s.t.} \quad & x_0 = s, \\
& x_{k+1} = f_\phi^{\mathrm{MPC}}(x_k, u_k), \ 0 \le k < N, \\
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& 0 \le \tilde{h}_\phi^{\mathrm{MPC}}(x_N).
\end{aligned}
$$

Parameters $\phi$ can affect the objective $L_\phi$, the dynamics $f_\phi^{\mathrm{MPC}}$, and the constraints $h_\phi^{\mathrm{MPC}}$.

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open-source software package providing state-of-the-art algorithms for optimal control

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- nonlinear & symbolic models via `CasADi`
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- Integrators for ODE & DAE: ERK & IRK, efficient sensitivity propagation
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- full & partial condensing via HPIPM

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- Exploit convex-over-nonlinear structures
- Customize the solver by providing a tailored Hessian or Jacobian approximation

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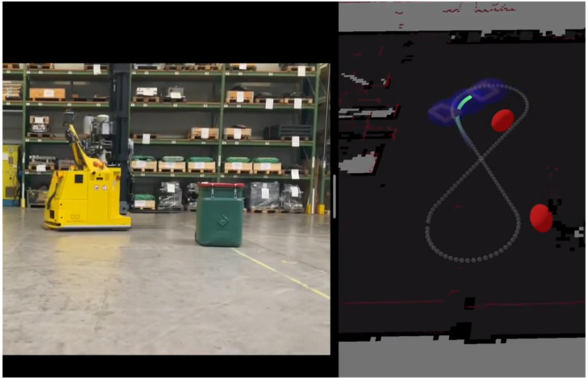
⭐ `github.com/acados/acados` 📚 `docs.acados.org` 🤝 `discourse.acados.org`

# acados in practice

- Mobile robotics with obstacle avoidance



(Subash et al., 2024)

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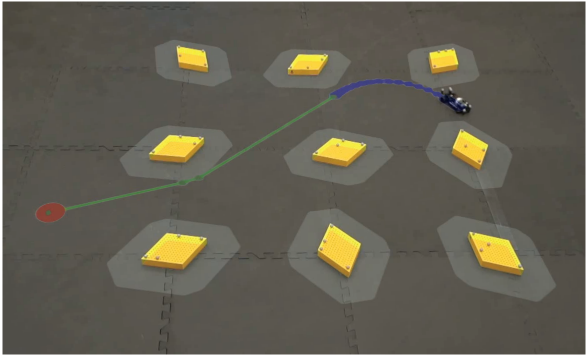

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# acados in practice

- Mobile robotics with obstacle avoidance
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(Romero et al., 2022)

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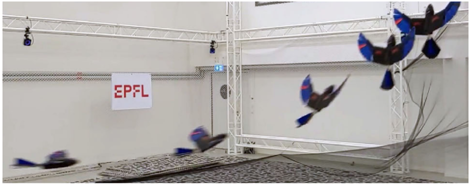


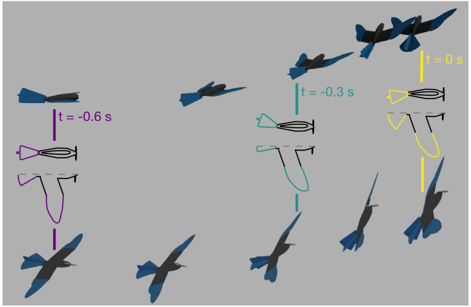


(Wüest et al., 2024)

# acados in practice

- Mobile robotics with obstacle avoidance
- Flight control for quadrotors and bird-like drones
- Autonomous e-scooters

(Meister et al., 2025)

## Parameterized OCP with parameters $\phi$.

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**Short notation:**

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\begin{aligned}
z^{\mathrm{sol}}(\phi) := \arg \min_{z \in \mathbb{R}^{n_z}} \quad & f(z;\phi) \\
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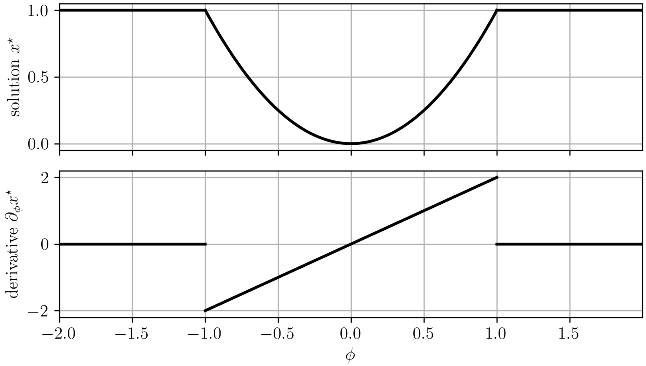
Wanted: $\frac{\partial z^{\mathrm{sol}}}{\partial \phi}(\phi)$ 🤠💰

# Illustrative example

## Scalar example

$$\min_x \quad (x - \phi^2)^2$$
$$\text{s.t.} \quad -1 \le x \le 1.$$



# KKT conditions & smoothing

Parametric optimization problem.

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## KKT conditions

$$
\begin{aligned}
\nabla_z f(z;\phi) + \nabla_z g(z;\phi)\lambda + \nabla_z h(z;\phi)\mu &= 0, \\
g(z;\phi) &= 0, \\
h(z;\phi) &\leq 0, \\
\mu &\geq 0, \\
\mu_i h_i(z;\phi) &= 0, \; i = 1, \dots, n_h.
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## Interior-point smoothed KKT conditions.

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g(z;\phi) &= 0, \\
h(z;\phi) &\le 0, \\
\mu &\ge 0, \\
\mu_i h_i(z;\phi) &= \tau, \; i = 1, \dots, n_h.
\end{aligned}
$$

Interior-point methods (IPM) solve this for $\tau \to 0$, e.g. `IPOPT`, `HPIPM`, `FORCES`, `Clarabel`, `fmincon`, ...

# The implicit function theorem

## Regularity assumptions.

- $f, g, h$ are twice differentiable in $z$ and once differentiable in $\phi$.
- $z^\star = z^{\text{sol}}(\bar{\phi})$ is a KKT point of the parametric NLP with parameter $\bar{\phi}$ satisfying LICQ, SOSC, and strict complementarity.

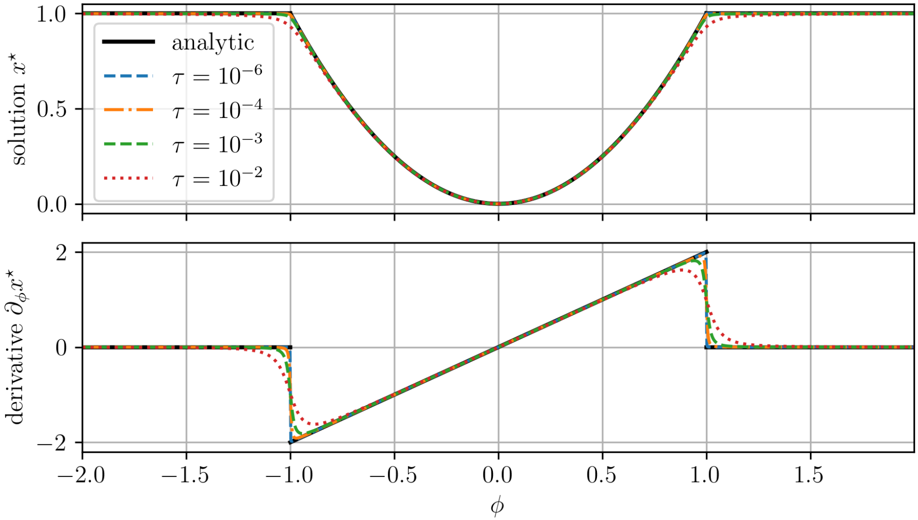
## Differentiable solution map.

If SOSC holds at $z^*$ with respect to the barrier problem with barrier parameter $\tau > 0$, the implicit function theorem implies that

1. There exists a solution of the smoothed interior-point KKT system $z_{\text{IPM}}^{\text{sol}}(\tau; \bar{\phi})$ with $\lim_{\tau \to 0^+} z_{\text{IPM}}^{\text{sol}}(\tau, \bar{\phi}) = z^\star$ and $\|z_{\text{IPM}}^{\text{sol}}(\tau; \bar{\phi}) - z^\star\| \in \mathcal{O}(\tau)$.
2. In a neighborhood of $\bar{\phi}$, there exists a differentiable function $v(\tau; \phi) = (z(\tau; \phi), \lambda(\tau; \phi), \mu(\tau; \phi))$ that corresponds to a locally unique solution of the smoothed interior-point KKT system.

Proofs are given in Pirnay, López-Negrete, and Biegler (2012); Wright (1992).

# Illustrative example



# Implementation in acados

**Nominal solution.** Smoothed interior-point KKT system is solved by iteratively solving quadratic barrier problems (barrier QPs):

1. Approximate the NLP by a QP.
2. Solve the smoothed interior-point KKT system associated with the QP with an interior-point solver for $\tau \to \bar{\tau}$ with $\bar{\tau} > 0$.

Equivalent to SQP with interior-point QP solver if $\bar{\tau} = 0$.

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**Solution sensitivities.** A linear system with the same matrix as for the nominal solution needs to be solved.

⏩ Reuse efficient implementation via Riccati recursion provided by `HPIPM` (Frison & Diehl, 2020) exploiting the OCP structure.

# Hessian approximations & two-solver approach

**Hessian approximations in SQP.**

- (generalized and extended) Gauss-Newton Hessian
  (Messerer et al., 2021; Baumgärtner & Diehl, 2022)
- regularization techniques such as project, mirror, Levenberg-Marquardt, convexify
  (Verschueren et al., 2017)

Benefits are reduced computational complexity and convex QP subproblems.

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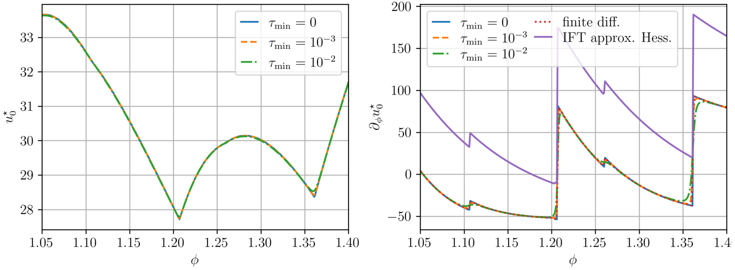

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**🤸 Nominal solver**

Solve nominal problem using any algorithm.

- Hessian approximation
- regularization
- ...

**🧮 Sensitivity solver**

- Evaluate exact Hessian.
- Compute solution sensitivity via efficient linear solve based on the Riccati recursion provided by `HPIPM`.

# Forward vs. adjoint sensitivities

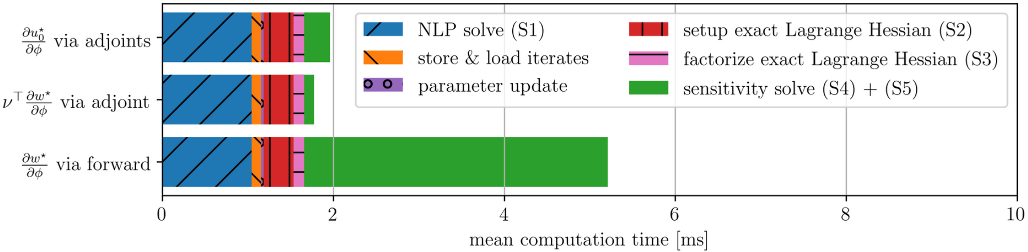


Figure: Computation times for a nominal solve plus forward or adjoint sensitivities. In this example, $n_x = 9$, $n_u = 3$, $n_\phi = 113$, $N = 40$

**Forward sensitivity.** Compute full Jacobian $\frac{\partial w^\star}{\partial \phi} \in \mathbb{R}^{n_w \times n_\phi}$.

**Adjoint sensitivity.** Compute single adjoint direction $\nu^\top \frac{\partial w^\star}{\partial \phi} \in \mathbb{R}^{1 \times n_\phi}$. $\leftarrow$ backpropagation

Here, $w^\star = (z^\star, \lambda^\star, \mu^\star)$.

# Benchmark Results

Table: Timings in [ms] for solving $n_{\text{batch}} = 128$ bounded LQR problems with $N = 20$, $n_x = 8$, $n_u = 4$, $n_\phi = 248$. In parentheses are multiples of the acados runtime.

| | Nominal solution | | | Solution + adjoint sens. | | |
|---|---|---|---|---|---|---|
| $u_{\max}$ | `acados` | `mpc.pytorch` | `cvxpygen` | `acados` | `mpc.pytorch` | `cvxpygen` |
| $10^4$ | 8.5 | 78 ($\times 9.2$) | 262 ($\times 31$) | 34.5 | 125 ($\times 3.6$) | 658 ($\times 19$) |
| 1.0 | 17.6 | 21024 ($\times 1200$) | 6402 ($\times 360$) | 42.0 | 21899 ($\times 520$) | 6845 ($\times 160$) |

Remark: `mpc.pytorch` is not faster on GPU than CPU (both in our experiments and in Adabag et al. (2025))

# Summary

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**Thanks for your attention!** 🙏
Looking forward to questions, discussions and collaborations!

**Preprint.** Jonathan Frey, Katrin Baumgärtner, Gianluca Frison, Dirk Reinhardt, Jasper Hoffmann, Leonard Fichtner, Sebastien Gros, Moritz Diehl: *Differentiable Nonlinear Model Predictive Control* (arxiv link)

**Code for figures and benchmark.** GitHub repository

⭐ Give us a star on GitHub: `github.com/acados/acados` ⭐

# Related work: no other differentiable solver tailored to OCPs with inequality support

| Software / publication | OCP-tailored | adjoints | ineq. support | Nonlinearity in cost & constraints | exact results | parallelization | permissive license | |
|---|---|---|---|---|---|---|---|---|
| `acados` | ✅ | ✅ | ✅ | ✅ | ✅ | `OpenMP` | ✅ | BSD-2 |
| `mpc.pytorch` (Amos et al., 2018) | ✅ | ✅ | ❌[a] | ❌ | ❌ | `PyTorch` | ✅ | MIT |
| `cvxpygen` + `cvxpylayers` (Schaller et al., 2022) (Schaller & Boyd, 2025) | ❌ | ✅ | ✅ | ⚪[b] | ✅ | `Python` multithreading | ✅ | Apache 2.0 |
| `diffmpc` (Toyota) (Adabag et al., 2025) | ✅ | ✅ | ❌ | ✅ | ❌ | `JAX` | ❌ | CC BY-NC-ND 4.0 |
| `trajax` (Google) no paper | ✅ | ✅ | ❌ | ✅ | ⚪[c] | `JAX` | ✅ | Apache 2.0 |
| `theseus` (Facebook) (Pineda et al., 2022) | ❌ | ✅ | ❌ | ❌ | ❌ | `PyTorch` | ✅ | MIT |
| `sIPOPT` (Pirnay et al., 2012)[d] | ❌ | ❌ | ✅ | ✅ | ✅ | – | ✅ | EPL |
| `CasADi` native (Andersson & Rawlings, 2018) | ❌ | ✅ | ✅ | ✅ | ✅ | – | ✅ | LGPL |

[a] while simple control bounds can be added, experiments revealed that the solver fails to converge if active set is nontrivial.
[b] only convex cost and constraints.
[c] a set of options seems to exist that allow using the exact Hessian. The documentation does not indicate in which case the sensitivities are accurate.
[d] functionality extremely limited in practice. Not usable in `CasADi` and abandoned rewrite effort in `https://github.com/athrpf/sipopt2`.

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