

Towards slow manifold based model reduction in optimal control of multiple time scale ODE

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Outline

- 1 Optimal Control
- 2 Singular Perturbed Problems
- 3 Model Reduction in Optimal Control

Optimal Control Problem (OCP)

$$\begin{aligned} \min_{z,u} \quad & E(z(T)) + \int_0^T L(z(t), u(t)) dt \\ \text{subject to} \quad & \dot{z}(t) = \tilde{f}(z(t), u(t)) \\ & 0 \leq s(z(t), u(t)) \\ & 0 \leq r(z(0), z(T)) \end{aligned}$$

where

- $z \in \mathbb{R}^{n_z}$ state variables
- $u \in \mathbb{R}^{n_u}$ control variables
- problem is often high-dimensional and stiff \rightsquigarrow Model Reduction

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Singular Perturbed Problem (SPP)

variables evolve on different time scales. Instead of $\dot{z}(t) = \tilde{f}(t, z(t))$, consider

SPP

$$\dot{x}(t) = f(x(t), y(t), u(t)) \quad (2a)$$

$$\varepsilon \dot{y}(t) = g(x(t), y(t), u(t)) \quad (2b)$$

with fixed $0 < \varepsilon \ll 1$.

Decomposition of variables:

- $z = (x, y)$ where x is a slow variable (also called reaction progress variable) and y is a fast variable.
- ε measure for time scale separation

Singular Perturbed Problem (SPP)

What happens in the limit $\varepsilon \rightarrow 0$?

SPP for $\varepsilon = 0$

$$\dot{x}(t) = f(x(t), y(t), u(t)) \quad (3a)$$

$$0 = g(x(t), y(t), u(t)) \quad (3b)$$

- \Rightarrow We get a system of differential algebraic equations (DAEs)! Can be seen as system of ODEs on manifold $M = \{g(x(t), y(t), u(t)) = 0\}$
- If partial derivative g_y is non-singular, use implicit function theorem: \exists function h such that $y = h(x, u)$. System becomes

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

Manifold also for $\varepsilon > 0$?

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Geometrically: Bundling of trajectories onto manifolds

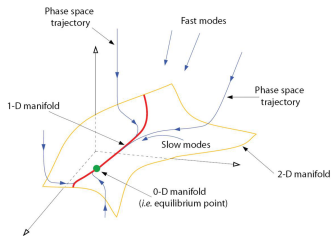


Figure : Courtesy of A.N. Al-Khateeb, J.M. Powers, S. Paloucci

Manifold also for $\varepsilon > 0$?

Geometrically: Bundling of trajectories onto manifolds

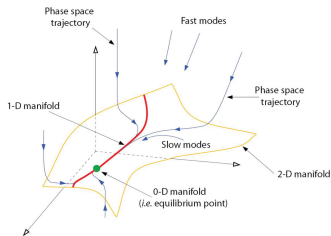


Figure : Courtesy of A.N. Al-Khateeb, J.M. Powers, S. Paloucci

Analytically, under some assumptions it holds

Theorem (Fenichel)

$\exists \varepsilon_0 > 0 \forall 0 < \varepsilon \leq \varepsilon_0$ there is a function $h(\cdot; \varepsilon) : K \subset \mathbb{R}^{n_x+n_u} \rightarrow \mathbb{R}^{n_y}$ such that

$$\mathcal{M}_\varepsilon := \{(x, y, u) : y = h(x, u; \varepsilon), (x, u) \in K\}$$

is locally invariant under the flow of (3).

Boundary Value Problem by Lebedz and Unger for calculation of $h(x^*, \varepsilon)$:

$$\min_{z(\cdot) = (x(\cdot), y(\cdot))} \quad \|\ddot{z}(t_0)\|_2^2 \quad (4a)$$

$$\text{s.t.} \quad \dot{z}(t) = \tilde{f}(t, z(t)), \quad t \in [t_0, t_f] \quad (4b)$$

$$0 = c(z(t)) \quad (4c)$$

$$x(t_f) = x^* \quad (4d)$$

where

- funktion c includes conservation of mass etc. (in case of chemical reactions)
- $\tilde{f} = (f, \frac{1}{\varepsilon}g)$
- $0 < t_f - t_0 \ll 1$

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OCP for singular perturbed systems

$$\begin{aligned} \min_{x,y,u} \quad & E(x(T), y(T)) + \int_0^T L(x(t), y(t), u(t)) dt \\ \text{subject to} \quad & \dot{x}(t) = f(t, x(t), y(t), u(t)) \\ & \varepsilon \dot{y}(t) = g(t, x(t), y(t), u(t)) \\ & 0 \leq s(x(t), y(t), u(t)) \\ & 0 \leq r(x(0), y(0), x(T), y(T)) \end{aligned}$$

with stiff dynamics (time scale separation)

reduced OCP

$$\begin{aligned} \min_{x,u} \quad & E(x(T), h(x(T), u(T), \varepsilon)) + \int_0^T L(x(t), h(x, u, \varepsilon), u(t)) dt \\ \text{subject to} \quad & \dot{x}(t) = f(t, x(t), h(x, u, \varepsilon), u(t)) \\ & 0 \leq s(x(t), h(x, u, \varepsilon), u(t)) \\ & 0 \leq r(x(0), h(x(0), u(0), \varepsilon), x(T), h(x(T), u(T), \varepsilon)) \end{aligned}$$

where

- reduced model order: $n_x + n_y \rightsquigarrow n_x$ state variables
- resulting ODE is less stiff

But still some issues

- strong dependence on efficient calculation of derivatives $\frac{\partial}{\partial x, u} h(x, u; \varepsilon)$ for solving the reduced OCP
- efficient coupling of calculation of the manifold and the OCP
- predecessor used two different tools:
 - ▶ DOT: tool for solving OCPs with multiple shooting approach around IPOPT
 - ▶ MoRe: tool for efficient calculation of manifold

Calculation of derivatives of h

Boundary value problem is transformed into NLP (with collocation or shooting method) with parameter $p \in \mathbb{R}^q$ (values for x^*, u)

$$\begin{aligned} (P(p)) \quad & \min_x && f(x, p) \\ & \text{s.t.} && g_i(x, p) \leq 0 \quad (i = 1, \dots, m) \\ & && g_i(x, p) = 0 \quad (i = m + 1, \dots, k) \end{aligned}$$

Sensitivity Theorem

Let \bar{x} be a local minimum of $P(p_0)$ satisfying LICQ and the second order sufficient conditions (SOSC) of the NLP $P(p_0)$ with strict complementarity and Lagrangian multipliers $\bar{\lambda}_i$. Then $\exists P_0 \subset \mathbb{R}^q$ open and \exists continuously differentiable functions $x : P_0 \rightarrow \mathbb{R}^n$, $\lambda_j : P_0 \rightarrow \mathbb{R}$ such that

- (i) $x(p_0) = \bar{x}$, $\lambda_j(p_0) = \bar{\lambda}_j$
- (ii) $x(p), \lambda_j(p)$ satisfy SOSC for $P(p)$ for all $p \in P_0$.

Calculation of derivatives of h (2)

Corollary

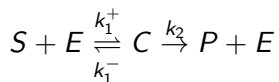
Denote the Lagrangian of $P(p)$ by $L(x, \lambda, p)$. Define $J(x) = \{1 \leq i \leq k : g_i(x, p) = 0\}$ and $G(x, p) := (g_i(x, p))_{i \in J(\bar{x})}$. Then it holds

$$\begin{pmatrix} x'(p_0) \\ \lambda'(p_0) \end{pmatrix} = \begin{pmatrix} \frac{d^2}{dx^2} L(\bar{x}, \bar{\lambda}, p_0) & \frac{d}{dx} G(\bar{x}, p_0)^T \\ \frac{d}{dx} G(\bar{x}, p_0) & 0 \end{pmatrix}^{-1} \cdot \begin{pmatrix} \frac{d^2}{dx dp} L(\bar{x}, \bar{\lambda}, p_0) \\ \frac{d}{dp} G(\bar{x}, p_0) \end{pmatrix}$$

\Rightarrow derivatives can be calculated with low extra costs.

results of my predecessor

Example (enzyme kinetics - Michaelis-Menten)



used for optimal control with artificial objective function:

$$\begin{aligned} \min_{x,y,u} \quad & \int_0^5 -50y + u^2 dt \\ \text{s.t.} \quad & \dot{x} = -x + (x + 0.5)y + u \\ & \varepsilon \dot{y} = x - (x + 1)y \\ & x(0) = 1, y(0) = \eta \end{aligned}$$

results of my predecessor (2)

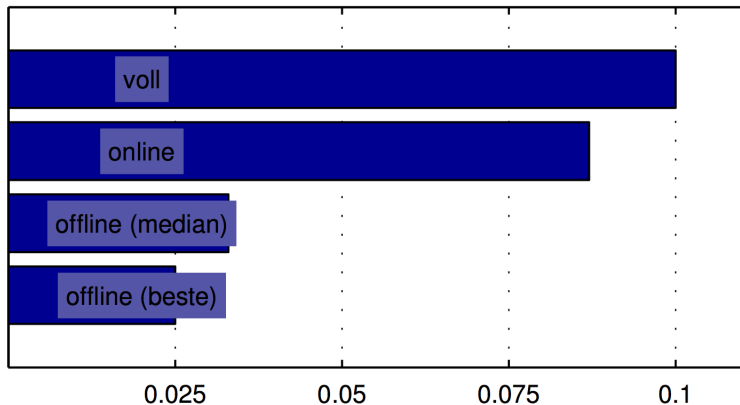


Figure : time in seconds for each iteration of the resulting NLP