ROBUST OPTIMIZATION FOR DYNAMIC SYSTEMS

Boris Houska

Outline of the Talk

- Uncertain Nonlinear Dynamic Systems
- Computation of Robust Positive Invariant Tubes
- Robust Optimization of Dynamic Systems
- Application: Robust Control of a Tubular Reactor
- Robust Optimization of Periodic Systems
- Open-Loop Stable Orbits of an Inverted Spring Pendulum
- Conclusions and Outlook

Uncertain Nonlinear Dynamic System

Notation:

• General uncertain system:

 $\forall \tau \in [t_1, t_2]: \dot{x}(\tau) = f(\tau, x(\tau), w(\tau)), x(t_1) = x_1.$

• Knowlegde about the uncertainty: $(x_1, w) \in \mathcal{W}$.

Uncertain Nonlinear Dynamic System

Notation:

• General uncertain system:

 $\forall \tau \in [t_1, t_2]: \dot{x}(\tau) = f(\tau, x(\tau), w(\tau)), x(t_1) = x_1.$

• Knowlegde about the uncertainty: $(x_1, w) \in \mathcal{W}$.

Definition of a Solution-Tube:

• The solution $X : [t_1, t_2] \to \Pi(\mathbb{R}^{n_x})$ is defined as:

$$X(t) := \begin{cases} x(t) \in \mathbb{R}^{n_x} & \exists x(\cdot), w(\cdot) : \\ \dot{x}(\tau) = f(\tau, x(\tau), w(\tau)) \\ (x(t_1), w) \in \mathcal{W} & \forall \tau \in [t_1, t] \end{cases}$$

Example 1

Scalar Linear System:

- $\dot{x} = ax + bw$ with $a, b, c \in \mathbb{R}$.
- $\mathcal{W} := \{ (x_1, w) \mid \forall t \in \mathbb{R} : -1 \leq w(t) \leq 1, x_1 = c \}.$

Visualization:



Example 2

Linear System with L_2 -bounded Uncertainty:

•
$$f(t, x, w) = Ax + Bw$$

•
$$\mathcal{W} := \left\{ (x_1, w) \mid x_1^2 + \int_{-\infty}^{\infty} \|w(\tau)\|_2^2 \, \mathrm{d}\tau \le 1 \right\}.$$

Visualization:



Solution:

• $X(t) = \mathcal{E}(Q(t))$ with

$$\dot{Q} = AQ + QA^T + BB^T$$

and $Q(t_1) = I$.

The Set Propagation Operator

Question:

• Can we build up the tube $X(\cdot)$ recursively?

The Set Propagation Operator

Question:

• Can we build up the tube $X(\cdot)$ recursively?

Assumption:

• $\mathcal{W} = \{ (x_1, w) \mid x_1 \in X_1, w(\tau) \in W(\tau) \quad \forall \tau \in \mathbb{R} \} .$

The Set Propagation Operator

Question:

• Can we build up the tube $X(\cdot)$ recursively?

Assumption:

• $\mathcal{W} = \{ (x_1, w) \mid x_1 \in X_1, w(\tau) \in W(\tau) \quad \forall \tau \in \mathbb{R} \}$.

Definition:

•
$$T(t_2, t_1)[X_1] := \begin{cases} y & \exists (x, w) : \\ \dot{x}(\tau) = f(\tau, x(\tau), w(\tau)) \\ w(\tau) \in W(\tau) \ \forall \tau \in [t_1, t_2] \\ x(t_1) \in X_1, \ x(t_2) = y \end{cases}$$

Associativity of the Set Propagation Operator

Associativity:

- $(T(t_4,t_3) \circ T(t_3,t_2)) \circ T(t_2,t_1) = T(t_4,t_3) \circ (T(t_3,t_2) \circ T(t_2,t_1))$.
- For automouos systems: $(\mathcal{T}, \circ) \cong (\mathbb{R}_+, +)$.

Associativity of the Set Propagation Operator

Associativity:

- $(T(t_4,t_3) \circ T(t_3,t_2)) \circ T(t_2,t_1) = T(t_4,t_3) \circ (T(t_3,t_2) \circ T(t_2,t_1))$.
- For automouos systems: $(\mathcal{T}, \circ) \cong (\mathbb{R}_+, +)$.

Infinitesimal Set Generation (Euler's method):

• $X(\tau + d\tau) := T(\tau + d\tau, \tau)[X(\tau)]$,

Associativity of the Set Propagation Operator

Associativity:

- $(T(t_4,t_3) \circ T(t_3,t_2)) \circ T(t_2,t_1) = T(t_4,t_3) \circ (T(t_3,t_2) \circ T(t_2,t_1))$.
- For automouos systems: $(\mathcal{T}, \circ) \cong (\mathbb{R}_+, +)$.

Infinitesimal Set Generation (Euler's method):

• $X(\tau + \mathrm{d}\tau) := T(\tau + \mathrm{d}\tau, \tau)[X(\tau)]$,

Formal Definition of a Set Valued ODE:

•
$$\forall \tau \in [t_1, t_2] : X(\tau^+) = F(\tau, X(\tau), W(\tau))$$

 $\forall \tau \in [t_1, t_2] : X(\tau) := T(\tau, t_1)[X(t_1)].$

Aim of the Talk

 Learn how to formulate and solve optimal control problems of the following form

 $\min_{u(\cdot),p,T_{e},X(\cdot)} \int_{0}^{T_{e}} \mathcal{L}(\tau, u(\tau), X(\tau), W(\tau)) \, \mathrm{d}\tau \, + \, M(\, p, T_{e}, X(T_{e})\,)$ s.t. $\begin{cases} X(\tau^{+}) = F(\tau, u(\tau), p, X(\tau), W(\tau)) \\ X(0) = X_{0} \\ 0 \geq H(\tau, u(\tau), p, X(\tau), W(\tau)) \end{cases}$

(for all $\tau \in [0, T_e]$).

Generalizations: Other boundary conditions (e.g. periodicity), etc.

Outline of the Talk

- Uncertain Nonlinear Dynamic Systems
- Computation of Robust Positive Invariant Tubes
- Robust Optimization of Dynamic Systems
- Application: Robust Control of a Tubular Reactor
- Robust Optimization of Periodic Systems
- Open-Loop Stable Orbits of an Inverted Spring Pendulum
- Conclusions and Outlook

Monotonicity of the Set Propagation Operator

Numerical Problem:

• Propagating $X(\tau^+) = F(\tau, X(\tau), W(\tau))$ expensive.

Monotonicity of the Set Propagation Operator

Numerical Problem:

• Propagating $X(\tau^+) = F(\tau, X(\tau), W(\tau))$ expensive.

Idea: Use Monotonicity

• $X \subseteq Y \Rightarrow T(t_2, t_1)[X] \subseteq T(t_2, t_1)[Y].$

Monotonicity of the Set Propagation Operator

Numerical Problem:

• Propagating $X(\tau^+) = F(\tau, X(\tau), W(\tau))$ expensive.

Idea: Use Monotonicity

• $X \subseteq Y \Rightarrow T(t_2, t_1)[X] \subseteq T(t_2, t_1)[Y].$

Definition:

 A function X : [t₁, t₂] → Π(ℝ^{n_x}) is called a robust positive invariant tube if

$$\forall \tau \in [t_1, t_2] : \quad \mathbb{X}(\tau^+) \supseteq F(\tau, \mathbb{X}(\tau), W(\tau)) .$$

Computational Methods for Linear Systems

Aim:

- Provide efficient methods for the computation of robust positive invariant tubes.
- Canditate sets: ellipsoids, polytopes, zonotopes, ...

Computational Methods for Linear Systems

Aim:

- Provide efficient methods for the computation of robust positive invariant tubes.
- Canditate sets: ellipsoids, polytopes, zonotopes, ...

Strategy:

• Start with analysis of linear system of the form

$$\forall \tau \in \mathbb{R} : \quad \dot{x}(\tau) = A(\tau)x(\tau) + B(\tau)w(\tau)$$

and generalize for nonlinear systems later.

Conservation Laws of Linear Uncer*tainty Propagation*

Proposition:

- Let A and B be L_1 -integrable, $X(t) := T(t, t_1)[X_1]$.
- If X_1 and $W(\tau)$ ($\tau \in [t_1, t]$) compact $\Rightarrow X(t)$ compact.
- If X_1 and $W(\tau)$ ($\tau \in [t_1, t]$) convex $\Rightarrow X(t)$ convex.
- If X_1 and $W(\tau)$ ($\tau \in [t_1, t]$) *-sym. $\Rightarrow X(t)$ *-sym.

Conservation Laws of Linear Uncer*tainty Propagation*

Proposition:

- Let A and B be L_1 -integrable, $X(t) := T(t, t_1)[X_1]$.
- If X_1 and $W(\tau)$ ($\tau \in [t_1, t]$) compact $\Rightarrow X(t)$ compact.
- If X_1 and $W(\tau)$ ($\tau \in [t_1, t]$) convex $\Rightarrow X(t)$ convex.
- If X_1 and $W(\tau)$ ($\tau \in [t_1, t]$) *-sym. $\Rightarrow X(t)$ *-sym.

Idea: Employ Techniques from Convex Analysis

- Given a compact and convex set $\mathcal{F} \subseteq \mathbb{R}^{n_x}$.
- Search lifted outer approximation $\mathcal{F} = \bigcap_{\lambda \in \mathbb{D}^+} \mathcal{F}^+(\lambda)$.

Example: Lifted Approximation of a Polytope

Problem:

- Given polytope $\mathcal{F} := \{ x \in \mathbb{R}^n \mid Ax \leq b \}, A \in \mathbb{R}^{m \times n}.$
- Construct a polytope with l < m facets which approximates \mathcal{F} from outside.

Example: Lifted Approximation of a Polytope

Problem:

- Given polytope $\mathcal{F} := \{ x \in \mathbb{R}^n \mid Ax \leq b \}, A \in \mathbb{R}^{m \times n}.$
- Construct a polytope with l < m facets which approximates \mathcal{F} from outside.

Solution:

- Take any $(m \times l)$ -matrix $\Lambda \in \mathbb{D}^+ := \{ \Lambda \mid \Lambda_{i,j} \geq 0 \}.$
- Choose $\mathcal{F}^+(\Lambda) := \{ x \mid C(\Lambda)x \leq d(\Lambda) \}$ with

$$C(\Lambda) := \Lambda^T A$$
 and $d(\Lambda) := \Lambda^T b$

• Then we have $\mathcal{F} = \bigcap_{\lambda \in \mathbb{D}^+} \mathcal{F}^+(\lambda)$.

Construction of Lifted Outer Approximations

General Technique:

• Support function of convex and compact set \mathcal{F} :

$$V(c) \ := \ \max_x \ c^T x \quad ext{s.t.} \quad x \in \mathcal{F} \ .$$

• Represent V by dual problem $V(c) = \inf_{\lambda \in \mathbb{D}^+} D(c, \lambda)$.

Construction of Lifted Outer Approximations

General Technique:

• Support function of convex and compact set \mathcal{F} :

$$V(c) := \max_{x} c^{T}x$$
 s.t. $x \in \mathcal{F}$.

- Represent V by dual problem $V(c) = \inf_{\lambda \in \mathbb{D}^+} D(c, \lambda)$.
- Define a parameterized outer approximation as

$$\forall \lambda \in \mathbb{D}^+ : \mathcal{F}^+(\lambda) := \bigcap_{c \in \mathbb{R}^n} \left\{ x \in \mathbb{R}^n \mid c^T x \leq D(c, \lambda) \right\} .$$

• No duality gap $\implies \mathcal{F} = \bigcap_{\lambda \in \mathbb{D}^+} \mathcal{F}^+(\lambda)$.

Problem:

• Find $Q \in \mathbb{S}_{++}^n$ with $\sum_{i=1}^N \mathcal{E}(Q_i) \subseteq \mathcal{E}(Q)$, $Q_i \in \mathbb{S}_+^n$ given.

Problem:

• Find $Q \in \mathbb{S}_{++}^n$ with $\sum_{i=1}^N \mathcal{E}(Q_i) \subseteq \mathcal{E}(Q)$, $Q_i \in \mathbb{S}_+^n$ given.

Motivation:

- Assume $x \in \mathcal{E}(Q_x)$ and $w \in \mathcal{E}(Q_w)$.
- Then $x^+ = G_x x + G_w w \in \mathcal{E}(G_x Q_x G_x^T) + \mathcal{E}(G_w Q_w G_w^T).$

Problem:

• Find $Q \in \mathbb{S}_{++}^n$ with $\sum_{i=1}^N \mathcal{E}(Q_i) \subseteq \mathcal{E}(Q)$, $Q_i \in \mathbb{S}_+^n$ given.

Motivation:

- Assume $x \in \mathcal{E}(Q_x)$ and $w \in \mathcal{E}(Q_w)$.
- Then $x^+ = G_x x + G_w w \in \mathcal{E}(G_x Q_x G_x^T) + \mathcal{E}(G_w Q_w G_w^T).$

Solution (Step 1):

$$V(c) = \max_{\substack{x_1, \dots, x_N \\ \lambda \ge 0}} c^T \left(\sum_{i=1}^N x_i \right) \text{ s.t. } x_i^T Q_i^{-1} x_i \le 1$$
$$= \inf_{\lambda \ge 0} \sum_{i=1}^N \frac{c^T Q_i c}{4\lambda_i} + \sum_{i=1}^N \lambda_i .$$

Problem:

• Find $Q \in \mathbb{S}_{++}^n$ with $\sum_{i=1}^N \mathcal{E}(Q_i) \subseteq \mathcal{E}(Q)$, $Q_i \in \mathbb{S}_+^n$ given.

Motivation:

- Assume $x \in \mathcal{E}(Q_x)$ and $w \in \mathcal{E}(Q_w)$.
- Then $x^+ = G_x x + G_w w \in \mathcal{E}(G_x Q_x G_x^T) + \mathcal{E}(G_w Q_w G_w^T).$

Solution (Step 2):

$$V(c) = \inf_{\lambda \ge 0} \sum_{i=1}^{N} \frac{c^{T}Q_{i}c}{4\lambda_{i}} + \sum_{i=1}^{N} \lambda_{i}$$

$$\mathbb{D}^{+} = \left\{ \lambda \in \mathbb{R}^{N} \mid \sum_{i=1}^{N} \lambda_{i} = 1 \right\}$$

$$\forall \lambda \in \mathbb{D}^{+} : \quad \mathcal{F}^{+}(\lambda) = \mathcal{E}\left(\sum_{i=1}^{N} \frac{1}{\lambda_{i}}Q_{i}\right) \supseteq \sum_{i=1}^{N} \mathcal{E}(Q_{i}) .$$

Back to Continous Time Systems...

Uncertain Linear System:

- $\dot{x}(t) = A(t)x(t) + B(t)w(t)$ with x(0) = 0
- Uncertainty assumption $||w(t)||_{\infty} \leq 1$ for all $t \in [0,T]$.

Back to Continous Time Systems...

Uncertain Linear System:

- $\dot{x}(t) = A(t)x(t) + B(t)w(t)$ with x(0) = 0
- Uncertainty assumption $||w(t)||_{\infty} \leq 1$ for all $t \in [0,T]$.

Example:



Back to Continous Time Systems...

Uncertain Linear System:

- $\dot{x}(t) = A(t)x(t) + B(t)w(t)$ with x(0) = 0
- Uncertainty assumption $||w(t)||_{\infty} \leq 1$ for all $t \in [0, T]$.

Example:





Example:

• The set X(t) for the linearized pendulum.

t [S]	<i>L</i> [m]	$g[{ m m}/{ m s}^2]$	m [kg]
1.2	1	9.81	1



Example:

• The set X(t) for the linearized pendulum.

t [s]	<i>L</i> [m]	$g[{ m m/s}^2]$	m [kg]
1.2	1	9.81	1

Question: How can we compute the set X(t) ?

Robust Optimization of Dynamic Systems - p. 17



Solution: Solve the LP

$$\max_{x(\cdot),w(\cdot)} c^T x(t)$$

s.t.
$$\begin{cases} \dot{x}(\tau) = A x(\tau) + B w(\tau) \\ x(0) = 0 \\ \|w(\tau)\|_{\infty} \le 1 \ \tau \in [0, t]. \end{cases}$$

for all directions c.

Question: How can we compute the set X(t) ?



CPU-time:

- Solve 100 LP's.
- Need approximately 1s for computing X(t).

Problem: Computing X(t) exactly takes very long if $n_x \gg 2$.

Strategy: Search for cheaper lifted outer approximations.
Example: Ellipsoidal Method

Assumption:

- $\Delta^n := \left\{ \lambda \in \mathbb{R}^n_{++} \mid \sum_{i=1}^n \lambda_i = 1 \right\}$
- $W(\tau) := \{ w \in \mathbb{R}^{n_w} \mid \forall \lambda \in \Delta^n : w \in \mathcal{E}(\Omega_\tau(\lambda)) \}$
- $\Omega_{\tau}: \mathbb{R}^{n}_{++} \to \mathbb{S}^{n_{w}}_{+}$ anti-homogeneous, i.e. $\Omega_{\tau}(\alpha \lambda) = \frac{1}{\alpha} \Omega_{\tau}(\lambda)$.

Example: Ellipsoidal Method

Assumption:

- $\Delta^n := \left\{ \lambda \in \mathbb{R}^n_{++} \mid \sum_{i=1}^n \lambda_i = 1 \right\}$
- $W(\tau) := \{ w \in \mathbb{R}^{n_w} \mid \forall \lambda \in \Delta^n : w \in \mathcal{E}(\Omega_\tau(\lambda)) \}$
- $\Omega_{\tau}: \mathbb{R}^{n}_{++} \to \mathbb{S}^{n_{w}}_{+}$ anti-homogeneous, i.e. $\Omega_{\tau}(\alpha \lambda) = \frac{1}{\alpha} \Omega_{\tau}(\lambda)$.

Theorem:

Let $Q: [t_1, t_2] \to \mathbb{S}^{n_x}_+$ and $\kappa: [t_1, t_2] \to \mathbb{R}^n_{++}$ be any functions satisfying

$$\dot{Q}(\tau) = A(\tau)Q(\tau) + Q(\tau)A(\tau)^T + \sum_{i=1}^n \kappa_i(\tau)Q(\tau) + B(\tau)\Omega_\tau(\kappa(\tau))B(\tau)^T$$

Then $\mathbb{X}(\cdot) := \mathcal{E}(Q(\cdot))$ is a robust positive invariant tube on $[t_1, t_2]$.

Visualization:



Application:

Visualization:



Application:

Visualization:



Application:

Visualization:



Application:

Visualization:



Application:

Visualization:



Application:

Visualization:



Application:

Visualization:



Application:

What about Nonlinear Dynamics? **Example:** Pendulum with uncertain forces $|w(t)| \leq 1$ N, $|v(t)| \leq 3$ N. ω [rad/s] SN 1 φ s_L 0 -1 m φ[rad] -0.5 0.5 0 $\begin{aligned} \dot{\varphi}(t) &= \omega(t) \\ \dot{\omega}(t) &= -\frac{g}{L}\sin(\varphi(t)) + \frac{\cos(\varphi(t))w(t) + \sin(\varphi(t))v(t)}{mL} \end{aligned}$

Robust Optimization of Dynamic Systems - p. 20

Strategy for Nonlinear Dynamics

General Strategy:

• Define a central path $q: [t_1,\infty) \to \mathbb{R}^{n_x}$ as

 $\forall \tau \in [t_1, \infty): \quad \dot{q}(\tau) = \varphi(\tau, q(\tau)) := f(\tau, q(\tau), 0), \quad q(t_1) = q_1.$

Decompose the system into linear and nonlinear parts

 $\dot{x}(\tau) = d(\tau) + A(\tau) \left(x(\tau) - q(\tau) \right) + B(\tau) w(\tau) + f_{\mathsf{n}}(\tau, q(\tau), x(\tau), w(\tau)).$

• Employ "lifted" overestimate for influence of the nonlinear terms f_n .

Strategy for Nonlinear Right-Hand Sides

Assumption (Ellipsoidal Method):

- There exists an explicit nonlinearity estimate Ω_{N} with

 $\forall \lambda \in \Delta^{m-n}: \quad f_{\mathsf{n}}\left(\tau, q(\tau), x(\tau), w(\tau)\right) \in \mathcal{E}\left(\ \Omega_{\mathsf{N}}(\tau, q(\tau), Q, \lambda)\ \right)$

for all $x(\tau) \in \mathcal{E}(Q, q(\tau))$, $w \in \mathcal{W}$, $\tau \in [t_1, \infty)$, and for all $Q \in \mathbb{S}^{n_x}_+$.

Strategy for Nonlinear Right-Hand Sides

Assumption (Ellipsoidal Method):

- There exists an explicit nonlinearity estimate Ω_{N} with

 $\forall \lambda \in \Delta^{m-n} : \quad f_{\mathsf{n}}\left(\tau, q(\tau), x(\tau), w(\tau)\right) \in \mathcal{E}\left(\Omega_{\mathsf{N}}(\tau, q(\tau), Q, \lambda)\right)$

for all $x(\tau) \in \mathcal{E}(Q, q(\tau))$, $w \in \mathcal{W}$, $\tau \in [t_1, \infty)$, and for all $Q \in \mathbb{S}^{n_x}_+$.

Strategy:

- Define $\Omega_{\text{total}}(\tau, q, Q, \kappa) := B(\tau)\Omega_{\tau}(\kappa^1)B(\tau)^T + \Omega_{\mathsf{N}}(\tau, q, Q, \kappa^2)$.
- Use $\Phi(\tau, q, Q, \kappa) := A(\tau)Q + QA(\tau)^T + \sum_{i=1}^m \kappa_i Q + \Omega_{\text{total}}(\tau, q, Q, \kappa)$.
- Now, if κ and Q are any functions which satisfy

$$\dot{Q}(\tau) = \Phi(\tau, q(\tau), Q(\tau), \kappa(\tau))$$

then $\mathbb{X}(\cdot) := \mathcal{E}(Q(\cdot), q(\cdot))$ is a robust positive invariant tube.

Examples for Nonlinearity Estimates

Example 1: Consider $f_{\mathsf{n},i}(\tau, q, x, w) = x^T C x$ with $C \succeq 0$. 1. $\Omega_{\mathsf{N}}(\tau, q(\tau), Q, \lambda) := [\operatorname{Tr}(QC)]^2 \operatorname{diag}(\lambda)^{-1}$. 2. $\Omega_{\mathsf{N}}(\tau, q(\tau), Q, \lambda) := \left[\sigma_{\mathsf{max}}\left(Q^{\frac{1}{2}}CQ^{\frac{1}{2}}\right)\right]^2 \operatorname{diag}(\lambda)^{-1}$.

Examples for Nonlinearity Estimates

Example 1: Consider $f_{\mathsf{n},i}(\tau, q, x, w) = x^T C x$ with $C \succeq 0$. 1. $\Omega_{\mathsf{N}}(\tau, q(\tau), Q, \lambda) := [\operatorname{Tr}(QC)]^2 \operatorname{diag}(\lambda)^{-1}$. 2. $\Omega_{\mathsf{N}}(\tau, q(\tau), Q, \lambda) := \left[\sigma_{\mathsf{max}}\left(Q^{\frac{1}{2}}CQ^{\frac{1}{2}}\right)\right]^2 \operatorname{diag}(\lambda)^{-1}$.

Example 2: $f_2(x,w) = -\frac{g}{L}\sin(x_1) + \frac{\cos(x_1)w_1 + 3\sin(x_1)w_2}{mL}$.

• On the domain $|x_1| \leq \frac{\pi}{2}$ may use

 $f_{\text{nonlinear},2}(x,w) \leq \chi(Q) := \frac{g}{L} \left[\sqrt{Q_{11}} - \sin(\sqrt{Q_{11}}) \right] + \frac{1 - \cos(\sqrt{Q_{11}}) + 3\sin(\sqrt{Q_{11}})}{mL}$ leading to the nonlinearity estimate $\Omega_{\text{N}} := \frac{1}{\lambda} \begin{pmatrix} 0 & 0 \\ 0 & \chi(Q)^2 \end{pmatrix}$.



- Use theorem to generate ellipsoidal outer approximation of the set X(t).
- The dual control input κ can be optimized for different directions.

$$\Omega_{\mathsf{N}}(t, q(t), Q, \kappa) := \begin{pmatrix} 0 & 0 \\ 0 & \frac{1}{\kappa} \left[\frac{g}{L} \left[\sqrt{Q_{11}} - \sin(\sqrt{Q_{11}}) \right] + \frac{1 - \cos(\sqrt{Q_{11}}) + 3\sin(\sqrt{Q_{11}})}{mL} \right]^2 \end{pmatrix}$$



- Use theorem to generate ellipsoidal outer approximation of the set X(t).
- The dual control input κ can be optimized for different directions.

$$\Omega_{\mathsf{N}}(t, q(t), Q, \kappa) := \begin{pmatrix} 0 & 0 \\ 0 & \frac{1}{\kappa} \left[\frac{g}{L} \left[\sqrt{Q_{11}} - \sin(\sqrt{Q_{11}}) \right] + \frac{1 - \cos(\sqrt{Q_{11}}) + 3\sin(\sqrt{Q_{11}})}{mL} \right]^2 \end{pmatrix}$$



- Use theorem to generate ellipsoidal outer approximation of the set X(t).
- The dual control input κ can be optimized for different directions.

$$\Omega_{\mathsf{N}}(t, q(t), Q, \kappa) := \begin{pmatrix} 0 & 0 \\ 0 & \frac{1}{\kappa} \left[\frac{g}{L} \left[\sqrt{Q_{11}} - \sin(\sqrt{Q_{11}}) \right] + \frac{1 - \cos(\sqrt{Q_{11}}) + 3\sin(\sqrt{Q_{11}})}{mL} \right]^2 \end{pmatrix}$$



- Use theorem to generate ellipsoidal outer approximation of the set X(t).
- The dual control input κ can be optimized for different directions.

$$\Omega_{\mathsf{N}}(t, q(t), Q, \kappa) := \begin{pmatrix} 0 & 0 \\ 0 & \frac{1}{\kappa} \left[\frac{g}{L} \left[\sqrt{Q_{11}} - \sin(\sqrt{Q_{11}}) \right] + \frac{1 - \cos(\sqrt{Q_{11}}) + 3\sin(\sqrt{Q_{11}})}{mL} \right]^2 \end{pmatrix}$$

Outline of the Talk

- Uncertain Nonlinear Dynamic Systems
- Computation of Robust Positive Invariant Tubes
- Robust Optimization of Dynamic Systems
- Application: Robust Control of a Tubular Reactor
- Robust Optimization of Periodic Systems
- Open-Loop Stable Orbits of an Inverted Spring Pendulum
- Conclusions and Outlook

Formulation of Robust Optimal Control Problems

Problem Formulation:

• Let us start with a robust optimal control problem of the form:

 $\min_{u(\cdot),p,T_{e},X(\cdot)} M(p,T_{e},X(T_{e}))$ s.t. $\begin{cases} X(\tau^{+}) = F(\tau,u(\tau),p,X(\tau),W(\tau)) \\ X(0) = X_{0} \\ 0 \geq H(\tau,u(\tau),p,X(\tau),W(\tau)) \end{cases}$

• Aim: Solve the above problem in a conservative approximation.

Definition of Monotonicity

Definition:

A function Z : Π(ℝ^{n_x}) → ℝ is monotonically increasing, if for any sets X, Y ⊆ ℝ^{n_x} with X ⊆ Y, we have that Z(X) ≤ Z(Y).

Definition of Monotonicity

Definition:

• A function $Z : \Pi(\mathbb{R}^{n_x}) \to \mathbb{R}$ is monotonically increasing, if for any sets $X, Y \subseteq \mathbb{R}^{n_x}$ with $X \subseteq Y$, we have that $Z(X) \leq Z(Y)$.

Assumptions:

- 1. The Mayer term $M(p, T_e, X(T_e))$ is mononically increasing with respect to the variable $X(T_e)$.
- 2. The constraint function $H(\tau, u(\tau), p, X(\tau), W(\tau))$ is componentwise mononically increasing in $X(\tau)$.

Definition of Monotonicity

Definition:

A function Z : Π(ℝ^{n_x}) → ℝ is monotonically increasing, if for any sets X, Y ⊆ ℝ^{n_x} with X ⊆ Y, we have that Z(X) ≤ Z(Y).

Assumptions:

- 1. The Mayer term $M(p, T_e, X(T_e))$ is mononically increasing with respect to the variable $X(T_e)$.
- 2. The constraint function $H(\tau, u(\tau), p, X(\tau), W(\tau))$ is componentwise mononically increasing in $X(\tau)$.

Question:

• Are the above assumption reasonable?

Example: Robust Counterpart Formulations

Robust Mayer Term:

- Assume nominal Mayer term $m : \mathbb{R}^{n_p} \times \mathbb{R}_+ \times \mathbb{R}^{n_x} \to \mathbb{R}$ is given.
- Define $M(p, T_{e}, X(T_{e})) := \sup_{x \in X(T_{e})} m(p, T_{e}, x).$
- M is monotonically increasing in $X(T_e)$.

Example: Robust Counterpart Formulations

Robust Mayer Term:

- Assume nominal Mayer term $m : \mathbb{R}^{n_p} \times \mathbb{R}_+ \times \mathbb{R}^{n_x} \to \mathbb{R}$ is given.
- Define $M(p, T_{e}, X(T_{e})) := \sup_{x \in X(T_{e})} m(p, T_{e}, x).$
- *M* is monotonically increasing in $X(T_e)$.

Robust Constraint Function:

• Analogous formulation of a constraint:

$$\begin{split} H_i(\tau, u(\tau), p, X(\tau), W(\tau)) &:= & \sup \quad h_i(\,\tau, \, u(\tau), \, p, \, x, \, w \,) \; . \\ & x \in X(\tau) \\ & w \in W(\tau) \end{split}$$

Example: Robustness Design Criteria

Minimize Maximum Distance of Two Points in the Terminal Set:

•
$$M(p, T_{e}, X(T_{e})) := \operatorname{diag}(X(T_{e})) := \sup_{x,y \in X(T_{e})} ||x - y||$$
.

• *M* is monotonically increasing in $X(T_e)$.

Example: Robustness Design Criteria

Minimize Maximum Distance of Two Points in the Terminal Set:

- $M(p, T_{e}, X(T_{e})) := \operatorname{diag}(X(T_{e})) := \sup_{x,y \in X(T_{e})} ||x y||$.
- *M* is monotonically increasing in $X(T_e)$.

Minimize the Inertia of the Terminal Set:

•
$$M(p, T_{\rm e}, X(T_{\rm e})) := \int_{X(T_{\rm e})} \left\| x - \int_{X(T_{\rm e})} x \, \mathrm{d}x \right\|^2 \, \mathrm{d}x$$

• M is monotonically increasing in $X(T_{\rm e})$.

Example: Robustness Design Criteria

Minimize Maximum Distance of Two Points in the Terminal Set:

- $M(p, T_{e}, X(T_{e})) := \operatorname{diag}(X(T_{e})) := \sup_{x,y \in X(T_{e})} ||x y||$.
- *M* is monotonically increasing in $X(T_e)$.

Minimize the Inertia of the Terminal Set:

•
$$M(p, T_{\rm e}, X(T_{\rm e})) := \int_{X(T_{\rm e})} \left\| x - \int_{X(T_{\rm e})} x \, \mathrm{d}x \right\|^2 \, \mathrm{d}x$$

• M is monotonically increasing in $X(T_{\rm e})$.

Minimize the Volume of the Terminal Set:

- $M(p, T_{\rm e}, X(T_{\rm e})) := \int_{X(T_{\rm e})} 1 \, \mathrm{d}x$.
- *M* is monotonically increasing in $X(T_e)$.

Ellipsoidal Approximation Assumption

Assumption:

• We have functions φ , Φ , q_0 , and Q_0 such that: for any function $\kappa : [0, T_e] \to \mathbb{R}^m_{++}$, and any vector $\kappa_0 \in \mathbb{R}^{n_0}_{++}$, which admit solutions $q : [0, T_e] \to \mathbb{R}^{n_x}$ and $Q : [0, T_e] \to \mathbb{S}^{n_x}_+$ of the coupled differential equation

$$\dot{q}(\tau) = \varphi(\tau, u(\tau), p, q(\tau), Q(\tau), \kappa(\tau)) \quad q(0) = q_0(\kappa_0)$$

$$\dot{Q}(\tau) = \Phi(\tau, u(\tau), p, q(\tau), Q(\tau), \kappa(\tau)) \quad Q(0) = Q_0(\kappa_0) ,$$

 $(\forall \tau \in [0, T_e])$ the set valued function $\mathbb{X}(\cdot) := \mathcal{E}(Q(\cdot), q(\cdot))$ is a robust positive invariant tube on the interval $[0, T_e]$ for which the condition $X_0 \subseteq \mathbb{X}(0)$ is also satisfied.

Ellipsoidal Approximation Strategy

Consider an auxiliary problem of the form

- If *H* is componentwise monotonically increasing: every feasible input (*u*, *p*) corresponds to a feasible point of the original problem.
- If additionally M is monotonically increasing: objective value of the above problem is an upper bound on exact objective value.

Outline of the Talk

- Uncertain Nonlinear Dynamic Systems
- Computation of Robust Positive Invariant Tubes
- Robust Optimization of Dynamic Systems
- Application: Robust Control of a Tubular Reactor
- Robust Optimization of Periodic Systems
- Open-Loop Stable Orbits of an Inverted Spring Pendulum
- Conclusions and Outlook

Nonlinear Jacketed Tubular Reactor (joint work with Filip Logist)

Model Equations:

- Consider tubular reactor with length L and perfect radial mixing.
- Assume: const. density & heat capacity of fluid, Arrhenius law.
- States: concentration and temperature

 $C(z) = C_{\mathsf{F}}(1 - x_1(z)) \quad T(z) = T_{\mathsf{F}}(1 + x_2(z)) - 273.15^{\circ}\mathsf{C}$

Nonlinear Jacketed Tubular Reactor (joint work with Filip Logist)

Model Equations:

- Consider tubular reactor with length L and perfect radial mixing.
- Assume: const. density & heat capacity of fluid, Arrhenius law.
- States: concentration and temperature

$$C(z) = C_{\mathsf{F}}(1 - x_1(z)) \quad T(z) = T_{\mathsf{F}}(1 + x_2(z)) - 273.15^{\circ}\mathsf{C}$$

• Steady state depends on the spatial coordinate $z \in [0, L]$:

$$\partial_z x_1(z) = (\alpha/v)(1 - x_1(z))e^{\frac{\gamma x_2(z)}{1 + x_2(z)}}$$

$$\partial_z x_2(z) = (\alpha \delta/v)(1 - x_1(z))e^{\frac{\gamma x_2(z)}{1 + x_2(z)}} + (\beta(z)/v)(u(z) - x_2(z))$$

• Jacket temperature u is controlled, heat transfer β is uncertain.

Nonlinear Jacketed Tubular Reactor (joint work with Filip Logist)

Aim: Maximize conversion, i.e minimize $m := C_F(1 - x_1(L))$ s.t.:

- model equations with $x_1(0) = 0$, $x_2(0) = 0$,
- control bounds, and maximum temperature constraint $T(z) \leq T_{\text{max}}$.


Nonlinear Jacketed Tubular Reactor (joint work with Filip Logist)

Aim: Maximize conversion, i.e minimize $m := C_F(1 - x_1(L))$ s.t.:

- model equations with $x_1(0) = 0$, $x_2(0) = 0$,
- control bounds, and maximum temperature constraint $T(z) \leq T_{\text{max}}$.



Robust Optimization of Dynamic Systems - p. 34

Aim:

• Find a nonlinearity estimate of the form

 $|f_i(q + \Delta x, w) - f_i(q, 0) - \partial_x f_i(q, 0) \Delta x - \partial_w f_i(q, 0) w| \le l_i(q, Q)$

for all w with $|w(t)| \leq 1$ and all $\Delta x \in \mathcal{E}(Q)$.

Aim:

• Find a nonlinearity estimate of the form

 $|f_i(q + \Delta x, w) - f_i(q, 0) - \partial_x f_i(q, 0) \Delta x - \partial_w f_i(q, 0) w| \le l_i(q, Q)$

for all w with $|w(t)| \leq 1$ and all $\Delta x \in \mathcal{E}(Q)$.

• Here:

$$f_1(x,w) = \frac{\alpha}{v}(1-x_1)e^{\frac{\gamma x_2}{1+x_2}}$$

$$f_2(x,w) = \frac{\alpha\delta}{v}(1-x_1)e^{\frac{\gamma x_2}{1+x_2}} + \frac{\beta_{\text{nominal}}(1+\Gamma w)}{v}(u-x_2)$$

Aim:

• Find a nonlinearity estimate of the form

 $|f_i(q + \Delta x, w) - f_i(q, 0) - \partial_x f_i(q, 0) \Delta x - \partial_w f_i(q, 0) w| \le l_i(q, Q)$

for all w with $|w(t)| \leq 1$ and all $\Delta x \in \mathcal{E}(Q)$.

• Here:

$$f_1(x,w) = \frac{\alpha}{v}(1-x_1)e^{\frac{\gamma x_2}{1+x_2}}$$

$$f_2(x,w) = \frac{\alpha\delta}{v}(1-x_1)e^{\frac{\gamma x_2}{1+x_2}} + \frac{\beta_{\text{nominal}}(1+\Gamma w)}{v}(u-x_2)$$

Main Idea: Use that $\forall y \in \mathbb{R}: e^y \leq 1 + y + \frac{y^2}{2}e^{|y|}$.

... and work out the details:

$$\begin{split} j(q,Q) &:= \frac{\gamma}{(1+q_2)(1+q_2-\sqrt{Q_{22}})} \\ r_1(q,Q) &:= j(q,Q) + \frac{\sqrt{Q_{22}}}{2} j(q,Q)^2 \exp(\sqrt{Q_{22}} |j(q,Q)|) \\ r_2(q,Q) &:= \frac{j(q,Q)}{1+q_2} + \frac{j(q,Q)^2}{2} \exp(\sqrt{Q_{22}} |j(q,Q)|) \\ l_1(q,Q) &:= \frac{\alpha}{v} \exp\left(\frac{\gamma q_2}{1+q_2}\right) \left[r_1(q,Q) \sqrt{Q_{11}Q_{22}} + r_2(q,Q) Q_{22} \right] \\ l_2(q,Q) &:= \delta l_1(q,u,Q) + \frac{\Gamma \beta_{\text{nominal}} \sqrt{Q_{22}}}{v} \quad \Omega_{\text{N}}(\lambda,q,Q) := \text{diag}(l_i(q,Q)/\lambda_i) \end{split}$$

... and work out the details:

$$\begin{split} j(q,Q) &:= \frac{\gamma}{(1+q_2)(1+q_2-\sqrt{Q_{22}})} \\ r_1(q,Q) &:= j(q,Q) + \frac{\sqrt{Q_{22}}}{2} j(q,Q)^2 \exp(\sqrt{Q_{22}} |j(q,Q)|) \\ r_2(q,Q) &:= \frac{j(q,Q)}{1+q_2} + \frac{j(q,Q)^2}{2} \exp(\sqrt{Q_{22}} |j(q,Q)|) \\ l_1(q,Q) &:= \frac{\alpha}{v} \exp\left(\frac{\gamma q_2}{1+q_2}\right) \left[r_1(q,Q) \sqrt{Q_{11}Q_{22}} + r_2(q,Q) Q_{22} \right] \\ l_2(q,Q) &:= \delta l_1(q,u,Q) + \frac{\Gamma\beta_{\text{nominal}}\sqrt{Q_{22}}}{v} \quad \Omega_{\text{N}}(\lambda,q,Q) := \text{diag}(l_i(q,Q)/\lambda_i) \end{split}$$

 This Nonlinearity Estimate enables us to robustly optimize the conversion such that the temperature constraint is satisfied for all possible uncertainties.

Robust Control of the Jacketed Tubular Reactor



- Constraints are guaranteed to be robustly satisfied.
- Simulation with 6% uncertainty remains in ellipsoidal tube.

Robust Control of the Jacketed Tubular Reactor



- Constraints are guaranteed to be robustly satisfied.
- Simulation with 6% uncertainty remains in ellipsoidal tube.

Outline of the Talk

- Uncertain Nonlinear Dynamic Systems
- Computation of Robust Positive Invariant Tubes
- Robust Optimization of Dynamic Systems
- Application: Robust Control of a Tubular Reactor
- Robust Optimization of Periodic Systems
- Open-Loop Stable Orbits of an Inverted Spring Pendulum
- Conclusions and Outlook

The Inverted Spring Pendulum



The Inverted Spring Pendulum

Model:

• Right-hand side function is given by

$$f(\xi, u, w) = \begin{pmatrix} v_x \\ v_y \\ -\frac{Dx}{m} \left(1 - \frac{L}{\sqrt{x^2 + y^2}}\right) - bv_x + w \\ -g + u - \frac{Dy}{m} \left(1 - \frac{L}{\sqrt{x^2 + y^2}}\right) - bv_y \\ v_z \\ u \end{pmatrix}$$

Optimal Control Problem

Aim:

• Find an open-loop stable periodic orbit at the "inverted" position.

Objective:

• Minimize the time-average over the maximum displacement of the mass point in *x*-direction:

$$\mathcal{L}(\tau, u(\tau), T_{e}, X(\tau), W(\tau)) := \max_{\xi \in X(\tau)} \frac{\left(e_{x}^{T} \xi\right)^{2}}{T_{e}}$$

with $e_x^T := (1, 0, ..., 0)^T \in \mathbb{R}^6$.

Optimization Variables:

• Set valued function X, control input u, end time T_e .

Optimal Control Problem

Constraints:

Periodic propagation of the uncertainty tube

 $X(\tau^+) = F(\tau, u(\tau), p, X(\tau), W(\tau))$ with $X(0) = X(T_e)$.

- Here: $W(\tau) = \{ w \in \mathbb{R} \mid \underline{w} \leq w \leq \overline{w} \}$
- Control and State Constraint Function:

$$H(\tau, u(\tau), X(\tau)) := \begin{pmatrix} u(\tau) - \overline{u} \\ -u(\tau) + \overline{u} \\ \max_{\xi \in X(\tau)} e_{v_z}^T \xi - \overline{v}_z \\ \min_{\xi \in X(\tau)} - e_{v_z}^T \xi + \overline{v}_z \end{pmatrix}$$

Optimization Results Based on Ellipsoidal Technique:



Summary

- "State" of uncertain systems is a set-valued function.
- Lifted set approximation techniques
- Ellipsoidal robust positive invariant tubes have desirable complexity.
- Formulation and Solution Techniques for Robust Optimal Control Problems
- Nonlinear application: robust control of a tubular reactor
- Existence of periodic tubes based in Schauder's fixed point theorem
- Open-loop stable orbits of an inverted pendulum