Simulation-aided Reachability and Local Gain Analysis for Nonlinear Dynamical Systems

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Abstract—We analyze reachability properties and local input/output gains of systems with polynomial vector fields. Upper bounds for the reachable set and nonlinear system gains are characterized by polynomial Lyapunov (storage) functions satisfying certain bilinear constraints. A methodology utilizing information from simulations to generate Lyapunov function candidates satisfying necessary conditions for bilinear constraints is proposed. The suitability of Lyapunov function candidates are assessed solving linear sum-of-squares optimization problems. Qualified candidates are used to compute upper bounds for the reachable set and nonlinear system gains and to initialize further coordinate-wise affine optimization. We illustrate the method on several examples from the literature.

I. INTRODUCTION

We consider the problem of computing upper bounds for the reachable set and local input-to-output (IO) gains of nonlinear dynamical systems with polynomial vector fields around asymptotically stable equilibrium points. Similar problems were studied in [1], [2], [3], [4], [5]. This paper is an extension of the work reported in [2] and proposes a methodology that incorporates prior information from simulations in reachability and local gain analysis of nonlinear systems.

Following [1], [2], we characterize upper bounds on the reachable sets and the local IO gains due to bounded $L_2$ (and possibly $L_\infty$) disturbances by Lyapunov (storage) functions which satisfy certain “local” dissipation inequalities [6]. Using sum-of-squares (SOS) relaxations for polynomial non-negativity [7], it is possible to search for polynomial Lyapunov functions for systems with polynomial (and/or rational) dynamics using semidefinite programming [3], [8], [1], [2]. However, the SOS relaxations for the problems in the papers lead to bilinear matrix inequality (BMI) constraints. Motivated by the difficulties associated with bilinear programming, we here propose a methodology that incorporates information from system simulations in formal proof construction (computing certifying Lyapunov functions) and extend the applicability of reachability and local IO gains analysis for nonlinear systems. Although the information from simulations is inconclusive, i.e., cannot be used to prove certain properties (such as upper bounds for reachable sets and local IO gains or lower bounds for regions-of-attraction) of the system, it provides insight into the system behavior. Following a similar technique developed for computing invariant subsets of the (robust) regions-of-attraction in [9], the method proposed here relaxes the regions-of-attraction (using a specific system theoretic interpretation of the corresponding optimization, specifically SOS optimization, problem) to a linear problem, and the true feasible set is a subset of the linear problem’s feasible set. If large amount of simulation data is used, samples from the linear problem’s feasible set often are suitable Lyapunov functions, i.e., provide suboptimal solutions for the actual problem, and certify certain upper bounds. They can also be used as initial seeds for further optimization (e.g. coordinate-wise linear search).

We demonstrate the development of the method for computing upper bounds for the reachable set due to bounded $L_2$ disturbances (or local $L_2 \rightarrow L_\infty$ gain) in detail and only comment on how to modify the method for computing upper bounds for local $L_2 \rightarrow L_2$ gain. The rest of the paper is organized as follows: Characterization of upper bounds for the reachable set with Lyapunov functions and a method for computing lower bounds are explained in section II. Section III is devoted to the simulation-based relaxation for the bilinear problem. The method is demonstrated on a few examples in section IV. Extensions of the simulation-aided technique to local $L_2 \rightarrow L_2$ gain analysis is discussed in section V, which is followed by concluding remarks.

Notation: $\mathbb{R}^n$ denotes the n-dimensional Euclidean space. For $Q = Q^T \in \mathbb{R}^{n \times n}$, $Q \succeq 0$ ($Q \succ 0$) means that $x^T Q x \geq 0$ ($x^T Q x > 0$) for all $x \in \mathbb{R}^n$. $\Re[x]$ represents the set of polynomials in $x$ of certain finite degree with real coefficients. The subset $\Sigma[x] := \{ \pi \in \Re[x] : \pi = \pi_1^2 + \pi_2^2 + \cdots + \pi_m^2, \pi_1, \ldots, \pi_m \in \Re[x] \}$ of $\Re[x]$ is the set of SOS polynomials. For $\pi \in \Re[x]$, $\partial(\pi)$ denotes the degree of $\pi$. We do not specify the degree of polynomials in $\Re[x]$ and $\Sigma[x]$, unless it causes confusion, and it is to be understood in the context.

II. REACHABLE SET DUE TO $L_2$ DISTURBANCES

Consider the nonlinear dynamical system

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

(1)

where $x(t) \in \mathbb{R}^n$, $w(t) \in \mathbb{R}^{n_w}$, and $f$ is a vector with elements in $\Re[\{x, w\}]$ such that $f(0, 0) = 0$. Let $\phi(t; \xi, w)$ denote the solution to (1) at time $t$ with the initial condition $x(0) = \xi$ driven by the input/disturbance $w$. The set $\Omega_\gamma$ of points reachable from the origin under (1), provided that the

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disturbance satisfies \( \|w\|_2^2 := \int_0^T w(t)^T w(t) \, dt \leq \gamma \), \( T \geq 0 \) is defined

\[
\Omega_\gamma := \{ \phi(T; 0, w) \in \mathbb{R}^n : T \geq 0, \|w\|_2^2 \leq \gamma \}.
\]

Next, we review characterizations of the upper and lower bounds of the reachable set.

A. Upper bound of the reachable set

Following a Lyapunov-like argument in [10, §6.1.1], Lemma 1 provides a characterization of sets containing \( \Omega_\gamma \).

For \( \gamma > 0 \) and a function \( V : \mathbb{R}^n \rightarrow \mathbb{R} \), define

\[
\Omega_{\gamma, V} := \{ \xi \in \mathbb{R}^n : V(\xi) \leq \gamma \}.
\]

**Lemma 1**: [1], [2] If a continuously differentiable function \( V \) satisfies

\[
V(x) > 0 \quad \text{for all} \quad x \in \mathbb{R}^n \setminus \{0\} \quad \text{with} \quad V(0) = 0,
\]

(2) \[ \frac{\partial V}{\partial x} f(x, w) \leq w^T w \quad \text{for all} \quad x \in \Omega_{\gamma, V}, w \in \mathbb{R}^{n_w}, \]

(3) then \( \Omega_{\gamma, V} \) contains \( \Omega_\gamma \).

In order to compute a tight upper bound for the reachable set by choice of \( V \), we introduce a fixed positive definite convex function \( p \) and a variable sized region \( P_\beta := \{ \xi \in \mathbb{R}^n : p(\xi) \leq \beta \} \) and minimize \( \beta \) imposing the constraint \( \Omega_{\gamma, V} \subseteq P_\beta \). This can be written as

\[
\min_{\beta > 0, V \in V} \beta \quad \text{subject to} \quad (2), (3), \quad \text{and} \quad \Omega_{\gamma, V} \subseteq P_\beta.
\]

Here \( V \) denotes the set of candidate Lyapunov functions over which the maximum is computed.

In order to make (4) amenable to numerical optimization (specifically SOS optimization), we restrict \( V \) and \( p \) to be all polynomials of some fixed degree and use the well-known sufficient condition for polynomial non-negativity: for a polynomial \( \pi \in \mathbb{R}[\xi] \) with \( \xi \in \mathbb{R}^n \), if \( \pi \in \Sigma[\xi] \), then \( \pi \) is positive semidefinite [7]. Using simple generalizations of the S-procedure (Lemma 3), we obtain sufficient conditions for the set containment constraint in (3). Specifically, let \( l_1 \) be a positive definite polynomial (typically \( \epsilon x^T x \) for some small real number \( \epsilon \)). Then, the constraint

\[
V - l_1 \in \Sigma[x]
\]

and \( V(0) = 0 \) are sufficient conditions for the constraints in (2). By Lemma 3, if \( s_1 \in \Sigma[x] \) and \( s_2 \in \Sigma(w, x) \), then

(\( \beta - p \)) (\( \gamma \) - \( V \)) \( s_1 \in \Sigma[x] \) and

(6)

\[
-[(\gamma - V) s_2 + \frac{\partial V}{\partial x} f(x, w) + w^T w] \in \Sigma[(x, w)]
\]

imply \( \Omega_{\gamma, V} \subseteq P_\beta \) and the constraint in (3), respectively. Using these sufficient conditions, an upper bound on optimal value of \( \beta \) in (4) can be defined as an optimization:

**Proposition 1**: Let \( \beta_B \) be defined as

\[
\beta_B(V_{\text{poly}}, S) := \min_{V, \beta, s_1, s_2} \beta \quad \text{subject to} \quad (5) - (7), \quad (8)
\]

\[
V(0) = 0, \quad V \in V_{\text{poly}}, \quad s_1 \subseteq S_1, \quad s_2 \subseteq S_2, \quad \text{and} \beta > 0.
\]

Here, \( V_{\text{poly}} \subset V \) and \( S \)‘s are prescribed finite-dimensional subspaces of \( \mathbb{R}[x] \) and \( \Sigma[x] \), respectively. Then, \( \beta_B(V_{\text{poly}}, S) \) is an upper bound for the optimal value of \( \beta \) in (4).

Although \( \beta_B \) depends on \( V_{\text{poly}} \) and \( S \), it will not always be explicitly notated. The optimization problem in (8) is bilinear because of the product terms \( V s_1 \) in (6) and \( V s_2 \) in (7). However, the problem has a more complex structure than a general BMI problem. If \( V \) is fixed, the problem becomes affine in \( s_1 \) and \( s_2 \) and vice versa. In section III, we will construct a convex outer bound on the set of feasible \( V \), sample from this outer bound set to obtain candidate \( V \)‘s, and then solve (8) for \( S \), holding \( V \) fixed. Construction of this outer bound on the set of feasible \( V \) relies on data provided by simulation trajectories of (1) driven by admissible disturbance signals. Next, we propose a method adapted from [11] for computing lower bounds of the reachable set. The input signals generated by this procedure will be used both in assessing the suboptimality of the upper bounds and in forming the simulation-based relaxation for the bilinear SOS problem (8).

B. Lower bound

For any positive \( T \), it follows that

\[
\max_{w \in \mathbb{E}[T] \setminus \{0\}} p(x(T)) \leq \max_{w \in \mathbb{E}[T] \setminus \{0\}} p(x(t)) \leq \beta_B. \quad (9)
\]

The conditions for stationarity of the finite horizon maximum in (9) are the existence of signals \( x, \lambda \) and \( w \) which satisfy \( \dot{x} = f(x, w), \|w\|_2^2 = \gamma, \lambda(T) = \frac{\partial p(x(T))^T}{\partial x}, \lambda(t) = -\frac{\partial f(x(t), w(t))^T}{\partial x} \lambda(t), \) and \( w(t) = \mu \frac{\partial f(x(t), w(t))^T}{\partial x} \lambda(t) \) for \( t \in [0, T] \), where \( \mu \) is chosen such that \( \|w\|_2^2 = \gamma \). Tierno et al. [11] proposed a power-like method to solve a similar maximization, and this method was adapted for computing lower bounds of the reachable set in [2]:

1) Pick \( T > 0 \) and \( w \) with \( \|w\|_2^2 = \gamma \).

2) Compute solution \( \phi(T; 0, w) \) of (1).

3) Set \( \lambda(T) = \frac{\partial p(x(T))^T}{\partial x} \).

4) Compute solution of \( \lambda(t) = -\frac{\partial f(x(t), w(t))^T}{\partial x} \lambda(t), \) and \( w(t) = \mu \frac{\partial f(x(t), w(t))^T}{\partial x} \lambda(t) \) for \( t \in [0, T] \),

5) Update \( w(t) = \mu \frac{\partial f(x(t), w(t))^T}{\partial x} \lambda(t) \).

6) Repeat steps (2) – (5) until \( w \) converges.

In practice, step (2) of each iteration gives a valid lower bound on maximum (over \( \|w\|_2^2 = \gamma \) of \( p(x(T)) \)), independent of whether the iteration converges.

III. SIMULATION BOUND RELAXATION FOR THE BILINEAR SOS PROBLEM

The usefulness of using simulation data in local stability analysis was demonstrated in [9] where a methodology that incorporates simulation data in formal proof construction for estimating the region-of-attraction of locally stable equilibrium points of autonomous dynamical systems with polynomial vector fields. In this section, we propose a similar technique for reachability analysis for nonlinear dynamical systems with polynomial vector fields. To this end, for given \( \beta > 0 \) and disturbance level \( \gamma > 0 \), let’s ask the question whether the reachable set \( \Omega_\gamma \) is contained in the set \( P_\beta \).

Certainly, just one disturbance signal \( w \) (with \( \|w\|_2^2 \leq \gamma \)) that leads to a system trajectory on which \( p \) takes on a value
larger than β certifies that Ωγ ⊈ Pβ. Conversely, a large collection of input signals w with ∥w∥2 ≤ γ that do not drive the system out of Pβ hints to the likelihood that indeed Ωγ ⊈ Pβ. In this latter case, let W be a finite collection of signals

\[ W := \left\{ (w, x) : \begin{array}{l}
  \text{w} \in L_2[0, \infty), \\
  \|w\|_2^2 \leq \gamma,
\end{array}
\right\}. \]

With β and γ fixed, the set of Lyapunov functions which certify that Ωγ ⊈ Pβ, using conditions (5)-(7), is simply \( \{ V \in \mathbb{R}[x] : (5) - (7) \text{ hold for some } s_i \in \Sigma[x] \} \). Of course, this set could be empty, but it must be contained in the convex set \( \{ V \in \mathbb{R}[x] : (10) \text{ holds} \} \), where

\[
(l_1(x(t))) \leq V(x(t)), \quad (10a) \\
V(x(t)) \leq \gamma, \quad (10b) \\
\frac{\partial V(x(t))}{\partial x} f(x(t), w(t)) \leq w(t)^T w(t) \quad (10c)
\]

for all \((w, x) \in W\) and \(t \geq 0\). Informally, these conditions simply say that, on the trajectories starting at the origin and driven by disturbance signals with \(\|w\|_2^2 \leq \gamma\), any \(V\) which verifies that \(\Omega_\gamma \subseteq P_\beta\) using the conditions (5)-(7) must take on values between 0 and \(\gamma\) and its rate of change along the corresponding system trajectory cannot exceed \(w(t)^T w(t)\).

A. Affine relaxation

Let \( \mathcal{V} \) be linearly parameterized as \( \mathcal{V} := \{ V \in \mathbb{R}[x] : V(x) = \varphi(x)^T \alpha \} \), where \(\alpha \in \mathbb{R}^n\) and \(\varphi\) is an \(n_\varphi\)-dimensional vector of polynomials in \(x\). Given \(\varphi(x)\), constraints in (10) can be viewed as constraints on \(\alpha \in \mathbb{R}^n\) yielding the convex set \(\{ \alpha \in \mathbb{R}^n : (10) \text{ holds for } V = \varphi(x)^T \alpha \} \). For each \((w, x) \in W\), let \(T_w\) be a finite subset of the interval \([0, \infty)\). A polytopic outer bound for this set described by finitely many constraints is \(\mathcal{V}_{sim} := \{ \alpha \in \mathbb{R}^n : (11) \text{ holds} \} \), where

\[
(l_1(x(t))) \leq \varphi(x(t))^T \alpha, \quad (11a) \\
\varphi(x(t))^T \alpha \leq \gamma, \quad (11b) \\
\frac{\partial \varphi(x(t))^T \alpha}{\partial x} f(x(t), w(t)) \leq w(t)^T w(t) \quad (11c)
\]

for all \((w, x) \in W\) and \(t \in T_w\).

The constraint that \(\frac{\partial \varphi(x)}{\partial x} f(x, w) \leq w^T w\) be satisfied on \(\gamma\) sublevel set of \(V\) and for all \(w\) implies that \(\frac{\partial \varphi(x)}{\partial x} f(x, w) \leq w^T w\) holds on a neighborhood of the origin in the \((x, w)\)-space. While it is possible to approximately impose this constraint on a sample in a small enough neighborhood of the origin, in some case (e.g. exponentially stable linearization) it is easy to analytically express as a constraint on the low order terms of the polynomial Lyapunov function. To this end, let \(\lambda > 1\) and \(P^T = P > 0\) be such that \(x^T P x\) is the quadratic part of \(V\) and define \(\text{Lin}(P)\) as

\[
\text{Lin}(P) := \left[ \frac{\partial \varphi(0)^T}{\partial x} P + P \frac{\partial \varphi(0)}{\partial x} \right] P \frac{\partial \varphi(0)(0)}{\partial w} - \lambda I \right].
\]

Then, if (3) holds, it must be

\[
\text{Lin}(P) \preceq 0, \quad (12)
\]

in other words, (12) is a necessary condition for (3) (consequently for (7)). Now, let \(\mathcal{V}_{lin} := \{ \alpha \in \mathbb{R}^n : P = P^T > 0\} \) and \(\text{Lin}(P) \preceq 0\). It is well-known that \(\mathcal{V}_{lin}\) is convex [10]. Furthermore, define \(\mathcal{V}_{SOS} := \{ \alpha \in \mathbb{R}^n : (5) \text{ holds} \} \). By [7], \(\mathcal{V}_{SOS}\) is convex. Since \(\mathcal{V}_{sim}, \mathcal{V}_{lin}\) and \(\mathcal{V}_{SOS}\) are convex, \(\mathcal{V} := \mathcal{V}_{sim} \cap \mathcal{V}_{lin} \cap \mathcal{V}_{SOS}\) is a convex set in \(\mathbb{R}^n\).

Equations (11) and (12) constitute a set of necessary conditions for (5)-(7); thus, we have \(\mathcal{V} \supseteq B := \{ \alpha \in \mathbb{R}^n : \exists s_1 \in \Sigma[x], s_2 \in \Sigma[(x, w)] \text{ such that } (5) - (7) \text{ hold} \} \). Since (6) and (7) are not jointly convex in \(V\) and the multipliers, \(B\) may not be a convex set and even may not be connected.

A point in \(\mathcal{V}\) can be computed solving an affine (feasibility) SDP with the constraints (5), (11) and (12). An arbitrary point in \(\mathcal{V}\) may or may not be in \(B\). However, if we generate a collection \(A := \{ \alpha(k) \}_{k=0}^{N_V-1} \) of \(N_V\) points distributed approximately uniformly in \(\mathcal{V}\), it may be that some of the points are in \(B\). To this end, we use the so-called “Hit-and-Run” (H&R) random point generation algorithm as described in [12].

B. Algorithms

Since an appropriate (feasible and not too conservative) value of \(\gamma\) is not known a priori, an iterative strategy to simulate and collect trajectories is necessary. This process when coupled with the H&R algorithm constitutes the Lyapunov function candidate generation.

Simulation and Lyapunov function generation (SimLFG)

Algorithm: Given positive definite convex \(p \in \mathbb{R}[x]\), a vector of polynomials \(\varphi(x)\), positive constants \(\beta, \gamma, N_{SIM} \) (integer), \(N_V \) (integer), \(\gamma_{shrink} \in (0, 1)\), and empty set \(W\).

1) Generate \(N_{SIM}\) input signals \(w\) with \(\|w\|_2^2 \leq \gamma\) and integrate (1) from the origin.

2) If all trajectories stay in \(P_\beta\), add the input signals and corresponding trajectories to \(W\) and go to step (3).

3) Find a feasible point for (5), (11) and (12). If (5), (11) and (12) are infeasible, set \(\gamma = \gamma_{shrink} \gamma\) and go to step (1).

4) Generate \(N_V\) Lyapunov function candidates using H&R algorithm, and return \(\gamma\) and Lyapunov function candidates.

Step (1) of SimLFG algorithm requires to generate input signals \(w\) with \(\|w\|_2^2 \leq \gamma\). In the current implementation of this algorithm, we use randomly generated piecewise constant input signals and signals generated by the method from section II-B using the given shape factor \(p\) and additional randomly generated shape factors.

The suitability of a Lyapunov function candidate is assessed by solving the optimization problem

Affine Problem: Given \(V \in \mathbb{R}[x]\) (from SimLFG algorithm), \(p \in \mathbb{R}[x]\), and \(\beta\), define

\[
\gamma_L := \max_{\gamma, s_1, s_2} \gamma \text{ subject to } \begin{array}{l}
  s_1, s_2 \in \Sigma[x], s_2 \in \Sigma[(x, w)], \gamma > 0, \\
  (\beta - p) - (\gamma - V) s_1 \in \Sigma[x], \\
  -((\gamma - V)s_2 + \frac{\partial \varphi}{\partial x} f(x, w) + w^T w) \in \Sigma[(x, w)].
\end{array}
\]

(13)
Although $\gamma^*_L$ depends on the allowable degree of $s_1$ and $s_2$, this is not explicitly noted. Note that for given $V$ and fixed $\gamma$, the problem in (13) is affine in the multipliers and can be solved as a linear SDP via a line search on the parameter $\gamma$.

Assuming Affine Problem is feasible, it is true that $\Omega_{\gamma,V} \subseteq \Omega_{\gamma_{\beta}} \subseteq \mathcal{P}_\beta$. The solution to Affine Problem provides a feasible point for the problem in (8). This feasible point can be further improved by solving the problem in (8) using iterative coordinate-wise affine optimization schemes, one of which is given next.

**Coordinate-wise optimization (CWOpt) algorithm:** Given $V \in \mathbb{R}[x]$, positive definite $l_1 \in \mathbb{R}[x]$, positive definite convex $p \in \mathbb{R}[x]$, a constant $\varepsilon_{\text{iter}} > 0$ (stopping tolerance), and maximum number of iterations $N_{\text{iter}}$, set $k = 0$

1) Solve Affine Problem.

2) Given $s_1$ and $s_2$ from step (1), solve (8) for $V$ and $\gamma$, and set $\gamma^*_L = \gamma^*_B$.

3) If $k = N_{\text{iter}}$ or the increase in $\gamma^*_L$ between successive applications of step (2) is less than $\varepsilon_{\text{iter}}$, return $V$ and $\gamma^*_L$. Otherwise, set $k$ to $k + 1$ and go to step (1).

Next, we review the following upper bound refinement procedure from [2] that is applied once a Lyapunov function $V$ and corresponding $\gamma$ satisfying the conditions in (5)-(7) are computed.

**Upper bound refinement from [2]:** Let $V$ and $\gamma$ satisfy (5)-(7), $m \geq 0$ be an integer, define $\epsilon := \gamma/m$, and partition the set $\Omega_{\gamma,V}$ into $m$ subregions $\Omega_{\gamma,V,k} := \{x \in \mathbb{R}^n : (k-1)\epsilon \leq V(x) \leq k\epsilon\}$ for $k = 1, \ldots, m$. If

$$\frac{\partial V}{\partial x} f(x, w) \leq h_k w^T w \text{ for all } x \in \Omega_{\gamma,V,k}, w \in \mathbb{R}^{n_w},$$

(14) holds for some $h_k > 0$, then for any $k \leq m$, the system in (1) with piecewise continuous $w$ starting from the origin satisfies

$$\int_0^T w^T w dt \leq \epsilon \left( \frac{1}{h_1} + \cdots + \frac{1}{h_m} \right) \Rightarrow V(\phi(T;0,w)) \leq k\epsilon.$$

Note that (14) already holds with $h_k = 1$. Therefore, it may be possible to make $\epsilon(1/h_1 + \cdots + 1/h_k)$ (in particular $k = m$) greater than $\gamma k/m$ (in particular $\gamma$) by minimizing $h_k$ such that (14) holds. S-procedure and SOS programming based sufficient conditions for (14) are proposed in [2].

**IV. EXAMPLES**

In the following examples, $l_1(x) = 10^{-6}x^T x$, $\partial(V) = 2$, $\partial(s_1) = 0$, $\partial(s_2) = 2$ ($s_2$ does not have constant and linear terms), $N_{\text{SIM}} = 1$ in Example 1 and 600 in Examples 2 and 3, $N_{\text{V}} = 1$ (in SimLFG algorithm), $\varepsilon_{\text{iter}} = 0.01$, $N_{\text{iter}} = 20$, and $m = 10$ (in the refinement procedure). We applied SimLFG and CWOpt algorithms for different but fixed values of $\beta$ and computed corresponding values of $\gamma$. Then, using the refinement procedure, new values $\gamma_{\text{refine}}$ of $\|w\|_2^2$ are computed such that $\Omega_{\gamma,V}$ contains the reachable set for disturbance signals $\|w\|_2^2 \leq \gamma_{\text{refine}}$. We also solved the problem of maximizing $\gamma$ subject to (5)-(7) for fixed values of $\beta$ using PENBMI. When there runs return a feasible solution, the optimal value of $\gamma$ is usually equal or close to

**Example 1:** Consider the nonlinear system from [1], [2]

$$\begin{align*}
\dot{x}_1 &= -x_1 + x_2 - x_1 x_2^2, & \dot{x}_2 &= u - x_1^2 x_2 + w, \\
y &= x_2, & u &= -y
\end{align*}$$

with $x_1(t), x_2(t), w(t) \in \mathcal{R}$ and $p(x) = x_1^2 + x_2^2$. Figure 1 shows the upper bounds for $\beta$ versus $\gamma$ before and after applying the refinement procedure and the lower bounds.

Next, we introduced $t_d = 0.4$ units of time delay at the input and modeled the delay using a (balanced) first order Padé approximation $\hat{x}_3(t) = -2/t_d x_3(t) + 2/\sqrt{t_d}p(t)$ and replaced the input by $u(t) = 2/\sqrt{t_d}x_3(t) + y(t)$, where $x_3(t) \in \mathcal{R}$, $x_3$ is the state of delay dynamics, and used $p(x) = x_1^2 + x_2^2 + 0.01x_3^2$. Figure 2 shows the upper and lower bounds for $\beta$ versus $\gamma$ before and after applying the refinement procedure.

**Example 2:** (Pendubot dynamics) The pendubot is an underactuated two-link pendulum with torque action only
on the first link. We designed an LQR controller to balance the two-link pendulum about its upright position. Third order polynomial approximation of the closed-loop dynamics with a disturbance signal inserted to the input signal is \( \dot{x}_1 = x_2, \) \( \dot{x}_2 = 45w + 782x_1 + 135x_2 + 689x_3 + 90x_4, \) \( \dot{x}_3 = x_4 \) and \( \dot{x}_4 = 279x_1x_2^2 + 273x_3^2 - 85w - 1425x_1 - 257x_2 - 1249x_3 - 171x_4. \) Here, \( x_1 \) and \( x_3 \) are angular positions of the first link and the second link (relative to the first link) and \( w \) is the scalar disturbance. Figure 3 shows the upper and lower bounds for \( \beta \) versus \( \gamma \) before and after applying the refinement procedure.

c) Example 3: (Controlled short period aircraft dynamics) Consider the plant dynamics

\[
\dot{x}_{AC} = \begin{bmatrix} -3 & -1.35 & -0.56 \\ 0.91 & -0.64 & -0.02 \\ 1 & 0 & 0 \\ 0.08x_1x_2 + 0.44x_2^2 + 0.01x_2x_3 + 0.22x_3^2 \\ -0.05x_2^2 + 0.11x_2x_3 - 0.05x_3^2 \\ 1.35 - 0.04x_2 \\ 0.4 \\ 0 \end{bmatrix} (u + w)
\]

(15)
y = [x_1, x_3]^T, where \( x_{AC} = [x_1, x_2, x_3]^T \) is the plant state, and \( x_1, x_2 \), and \( x_3 \) are the pitch rate, the angle of attack, and the pitch angle, respectively. The input \( u \) is the elevator deflection and determined by

\[
\dot{x}_C = \begin{bmatrix} -0.60 & 0.09 \\ 0 & 0 \\ 0 & 0 \\ -0.06 & 0.02 \\ -0.75 & -0.28 \end{bmatrix} x_C + \begin{bmatrix} -0.60 & 0.02 \\ -0.75 & -0.28 \end{bmatrix} y
\]

(16)
u = x_4 + 2.2x_5, where \( x_C = [x_4, x_5]^T \) is the controller state, and \( w(t) \in \mathcal{R} \) is the input disturbance. We applied the algorithms as described above with \( p(x) = x^T x \) and showed the upper and lower bounds before and after the refinement in Figure 4.

V. EXTENSIONS TO LOCAL \( \mathcal{L}_2 \rightarrow \mathcal{L}_2 \) GAIN ANALYSIS

We now discuss a straightforward extension of simulation-aided analysis for computing upper bounds for \( \mathcal{L}_2 \rightarrow \mathcal{L}_2 \) IO gains of nonlinear systems. Consider the dynamical system governed by

\[
\dot{x} = f(x, w) \quad \text{and} \quad z = h(x),
\]

(17)

where \( x, w, \) and \( f \) are as before and \( h \) is an \( n_z \)-vector of polynomials in \( x \) such that \( h(0) = 0 \). We use the following lemma characterizing an upper bound for the \( w \) to \( z \) induced \( \mathcal{L}_2 \rightarrow \mathcal{L}_2 \) gain of the system in (17) is proven in [2].

Lemma 2: If there exists a real scalar \( \kappa > 0 \) and a continuously differentiable function \( V \) such that

\[
V(0) = 0 \quad \text{and} \quad V(x) \geq 0,
\]

(18)

\[
\frac{\partial V}{\partial x} f(x, w) \leq w^T w - \frac{1}{\kappa} z^T z \quad \forall x \in \Omega_{1, V}, \text{ and } w \in \mathcal{R}^{n_w}
\]

(19)

then the system in (17) starting from the origin and \( \|w\|_2^2 \leq \gamma \), we have \( \|z\|_2^2 \leq \kappa \gamma \).

By Lemma 3, existence of \( s_3 \in \Sigma([x, w]) \) such that

\[
- (\gamma - V) s_3 + \frac{\partial V}{\partial x} f(x, w) - w^T w + \kappa z^T z \in \Sigma([x, w])
\]

(20)

implies (19). The constraint in (20) is bilinear with the similar structure to the constraint in (7) that it becomes affine in \( V \) with fixed \( s_3 \) and vice versa. Therefore, if we generate qualified Lyapunov function candidates, we can assess these functions solving affine SDPs or further optimize by using coordinate-wise affine schemes (similar to CWOpt for reachability analysis). To this end, let \( \kappa, \gamma > 0 \) be given and define \( G \) be a finite collection of signals

\[
G := \left\{ (w, x, z) : w \in \mathcal{L}_2[0, \infty), \|w\|_2^2 \leq \gamma, \|h(\phi(t; 0, w))\|_2^2 \leq \kappa \gamma \right\}
\]

Then, the conditions in (21) for \( (w, x, z) \in G \) and \( t \geq 0 \).

\[
0 \leq V(x(t)) \gamma 
\]

(21)
are necessary conditions for (20). These necessary conditions along with that on the linearized dynamics can be used to generate Lyapunov function candidates in a manner parallel to the SimLFG algorithm for reachability analysis.

VI. CONCLUSIONS

We analyzed reachability properties and local input/output gains of systems with polynomial vector fields. Upper bounds for the reachable set and nonlinear system gains are characterized with Lyapunov (storage) functions satisfying certain conditions. Finite dimensional polynomial parameterizations for Lyapunov functions were used. A methodology utilizing information from simulations to generate Lyapunov function candidates satisfying necessary conditions for bilinear constraints was proposed. The suitability of Lyapunov function candidates were assessed solving linear sum-of-squares optimization problems. Qualified candidates were used to compute upper bounds for the reachable set and nonlinear system gains and to initialize further coordinate-wise affine optimization. We illustrated the method on several examples from the literature.

VII. ACKNOWLEDGEMENTS

This work was sponsored (in part) by the Air Force Office of Scientific Research, USAF, under grant/contract number FA9550-05-1-0266. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the AFOSR or the U.S. Government. The authors would like to thank Timothy Wheeler for sharing his Matlab implementation of the algorithm explained in section II-B.

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