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Affine Parameter-Dependent Lyapunov Functions for LPV Systems with Affine Dependence

Pepijn B. Cox, Member, IEEE, Siep Weiland, Member, IEEE, and Roland Tóth, Senior Member, IEEE

Abstract—This paper deals with the certification problem for robust quadratic stability, robust state convergence, and robust quadratic performance of linear systems that exhibit bounded rates of variation in their parameters. We consider both continuous-time (CT) and discrete-time (DT) parameter-varying systems. In this paper, we provide a uniform method for this certification problem in both cases and we show that, contrary to what was claimed previously, the DT case requires a significantly different treatment compared to the existing CT results. In the established uniform approach, quadratic Lyapunov functions, that are affine in the parameter, are used to certify robust stability, robust convergence rates, and robust performance in terms of linear matrix inequality feasibility tests. To exemplify the procedure, we solve the certification problem for $L_2$-gain performance both in the CT and the DT cases. A numerical example is given to show that the proposed approach is less conservative than a method with slack variables.

Index Terms—Linear parameter-varying systems; Parameter-varying Lyapunov functions; Stability of linear systems; LMIs.

I. INTRODUCTION

The certification of stability and performance of a linear system against uncertain and/or time-varying parameters is of paramount interest [1]–[3]. Non-linear and/or non-stationary effects can be represented by varying dynamic behavior of a linear system description expressed as parameter variations. This makes the so-called linear parameter-varying (LPV) system representations widely applicable to model physical or chemical processes. However, the certification of robust quadratic stability, robust state convergence, and robust quadratic performance for LPV representations becomes more involved compared to the linear time-invariant (LTI) case. There has been extensive research in this area, where the parameter variations are assumed to be either time-invariant in a constraint set or time-varying signals with possible constraints on their values, rates of variations, bandwidths, or spectral contents. For time-invariant parametric dependence and arbitrary fast time-variations, a rich literature exists, e.g., see [3]–[5].

In a wide range of applications, systems exhibit bounded parameter variations and bounded rates of variation. For these systems, assumptions on arbitrary fast parameter rates are unrealistic and conservative. Formulation of stability conditions taking the bounded rate of variation into account can be accomplished, e.g., via integral-quadratic-constraints (IQC) [6]–[10] based on an equivalent linear fractional representation (LFR) of the LPV system. Lyapunov theory based on state-space representations or LFR forms [11]–[18], the quadratic separator theorem for LFRs [19]–[21], or Finsler’s Lemma [22]. However, these stability and performance formulations result in an infinite set of linear matrix inequalities (LMIs). To obtain tractable methodologies, a number of relaxation techniques can be applied. These include 1) vertex separation or convex-hull relaxation, including $\mu$ synthesis, $D/G$ scaling, and full-block multipliers, [6], [7], [9], [10], [19]–[21]; 2) partial-convexity arguments [11]–[13]; 3) sum-of-squares relaxation [21], [23]; 4) Pólya relaxation [8], [14]–[16]; 5) slack variable methods (applied in discrete-time) [14], [16], [17]; and 6) partitioning of the uncertainty space [1], [18].

The aforementioned overview is far from complete due to the vast amount of literature on this topic. A summary of various relaxation techniques in the continuous-time (CT) case is found in [3], [24].

Many approaches presented in the literature for quadratic stability, state convergence, and quadratic performance certification problems are either conservative or have a high computational demand due to the large number of free parameters or the large number of LMIs. Furthermore, the CT and the discrete-time (DT) cases are fundamentally different for these problems. Indeed, in the DT case, the robust stability analysis requires a significantly different relaxation technique leading to more involved synthesis and verification results. By neglecting this difference, the DT case remained mainly unexplored under the claims that it trivially follows from the CT results. We will demonstrate that this is not the case. The goal of this paper is to provide a unified method for certification of robust quadratic stability, robust state convergence, and robust quadratic performance, in both the CT and DT cases, for linear systems that exhibit parameter variations where these variations have bounded rates. The certification problem is solved using parameter-dependent Lyapunov functions. To avoid large numbers of free parameters, to decrease the number of LMIs, and to avoid conservativeness of the results, we apply the partial-convexity relaxation argument inspired by the results in [11]–[13].

More specifically, the contributions of the paper are the following, for the CT case, we extend [11], [12] to include a certificate on the exponential rate of decay of the state, independent of the uncertain parameter. For the DT case, we extend the partial-convexity argument to handle the third-order
terms of the Lyapunov function without introducing additional free parameters and we provide a less conservative robust stability test, a state convergence guarantee, and a performance test than other existing approaches. To the authors’ knowledge, the only contribution using the partial-convexity argument in the DT case is [13]. However, [13, Thm. 1] avoids the cubic dependencies on the parameters by including additional free parameters and by increasing the number of LMIs. Additionally, we draw a parallel with LMI regions to show why the DT case induces a more involved set of LMIs. In addition, an illustrative example is provided comparing the proposed partial-convexity results with a slack variable based method in the DT case.

The paper is organized as follows. In Section II, the concept of LPV systems, state-space representations, and the problem setting are introduced. The analysis on affine quadratic stability (AQS) is given in Section III. Section IV reveals how the partial-convexity relaxation of the AQS certification problem is the time-varying parameter (i.e., the time derivative of the state; and for the DT case, the only contribution using the partial-convexity argument in the CT case, denoted as $R^n$ denotes the initial state. In this paper, we consider the LPV state-space representation:

$$\xi(t) = A(p(t))x(t) + B(p(t))w(t),$$

$$z(t) = C(p(t))x(t) + D(p(t))w(t),$$

where $x : T \mapsto R^{n_x}$ is the state variable, $p : T \mapsto P \subseteq R^{n_p}$ is the time-varying parameter (i.e., the scheduling signal), $w : T \mapsto R^{n_w}$ is the general disturbance channel, $z : T \mapsto R^{n_z}$ denotes the performance channel, and $t \in T$ denotes time. For the CT case, $T = R$ and $\xi = \frac{dx}{dt}$, i.e., $\xi(x(t)) = \frac{dx}{dt} (x)$ denotes the time derivative of the state; and for the DT case, $T = Z$ and $\xi = q$ is the time-shift operator, i.e., $\xi(x(t)) = x(t+1)$. The parameter-varying matrix functions $A(\cdot), \ldots, D(\cdot)$ in (1) are considered to be affine functions of $p$:

$$A(p(t)) = A_0 + \sum_{i=1}^{n_p} A_i p_i(t),$$

$$B(p(t)) = B_0 + \sum_{i=1}^{n_p} B_i p_i(t),$$

$$C(p(t)) = C_0 + \sum_{i=1}^{n_p} C_i p_i(t),$$

$$D(p(t)) = D_0 + \sum_{i=1}^{n_p} D_i p_i(t),$$

with known matrices $A_i \in R^{n_x \times n_x}$, $B_i \in R^{n_x \times n_w}$, $C_i \in R^{n_z \times n_x}$, $D_i \in R^{n_z \times n_w}$ for $i = 0, \ldots, n_p$ and $p_i$ is the $i$-th element of the scheduling variable. Due to linearity from $x$ to $z$, asymptotic stability of (1) is dictated by stability of the fixed point at the origin of the autonomous part of (1), i.e.,

$$\xi(x(t)) = \frac{A(p(t))x(t)}{f(x(t),p(t))},$$

$$x(0) = x_0,$$

where $x_0 \in R^{n_x}$ denotes the initial state. In this paper, we assume that the scheduling variable and its rate are bounded:

A1 The scheduling signal $p(t)$ and its rate of variation $\delta p(t)$, defined by $\delta p(t) = \frac{dp(t)}{dt}$ in the CT case and $\delta p(t) = p(t+1) - p(t)$ in the DT case, range for all $t \in T$ in the bounded set $P \times V$, i.e., $(p(t), \delta p(t)) \in P \times V$ with $V \subseteq R^{n_p}$. Here $P = \text{co}(P)$ and $V = \text{co}(V)$ are defined as the convex hulls of the hyper-rectangles

$$P = \{ [v_1 \ldots v_n] : v_i \in [p_i, p_i + \text{P} ] \},$$

$$V = \{ [v_1 \ldots v_n] : v_i \in [\nu_i, \nu_i + \text{V} ] \},$$

with $2^n$ vertices each.

B. Notation

Let $R_v$ denote the set of intervals $\{s, s + 1, \ldots, v\}$ and $R^n$ the set of all $n \times n$ real symmetric matrices. The superscript $n$ is omitted if the dimension is not relevant for the context. In addition, the inequalities $A \succeq B$ and $A \succ B$ with $A \in R^n$ and $B \in R^n$ mean that $A - B$ is positive semi-definite and positive definite, respectively. Let $P_\nu$ denote the center of $P$:

$$P_\nu = \left[ \frac{p_1 + p_2}{2} \ldots \frac{p_n + p_{n+1}}{2} \right]^T.$$

In addition, we will denote multiple summations $\sum_{i=1}^{n_p} \sum_{k=1}^{n_q} X^{\frac{k}{2}}$ as the standard notation for the collection of all maps from $Z$ to $X$. $R \geq 0$ denotes the set of nonnegative real numbers and $Z_{\geq 0}$ is the set of nonnegative integers. $T_0 = R \geq 0$ in the CT case and $T_0 = Z_{\geq 0}$ in the DT case. With $\sigma_i(A)$, we denote the singular values of a real matrix $A$ where the largest and smallest singular values are denoted as $\sigma_{\max}(A)$ and $\sigma_{\min}(A)$, respectively. The eigenvalues of $A$ are denoted as $\lambda_i(A)$. The spectral norm of $A$ is defined as $\|A\|_2 = \sigma_{\max}(A)$. Furthermore, with $\|\cdot\|_q$ we denote the vector $q$-norm. The $L_q$-norm of a continuous signal $w$ is $\|w\|_q = (\int_0^\infty \|w(t)\|^q dt)^{1/q}$ and for a discrete signal $w$, the $\ell_q$-norm is $\|w\|_q = (\sum_{t=0}^\infty \|w(t)\|^q)^{1/q}$.

III. AFFINE QUADRATIC STABILITY

In this paper, asymptotic stability of (3) is verified under A1 by using a parameter-dependent Lyapunov function.

Definition 1 (Parameter-dependent Lyapunov function): The function $V : R^{n_x} \times P \rightarrow R$ is a parameter-dependent Lyapunov function for (3) if:

(i) $V(x, p) > 0$ for all $x \in R^{n_x}$ with $x \neq 0$ and $\forall p \in P$;

(ii) $V(x, p) = 0$ for $x = 0$ and $\forall p \in P$; and

(iii) $\Delta V(x, p, r) < 0$ for $\forall (x, p, r) \in R^{n_x} \times P \times V$ with $x \neq 0$.

In the CT case,

$$\Delta V(x, p, r) := \nabla_x V(x, p) \cdot f(x, p) + \nabla_p V(x, p) \cdot r;$$

where $\nabla_x$ indicates the gradient of a function w.r.t. $x$ and $\cdot$ is the inner product. For the DT case,

$$\Delta V(x, p, r) := V(f(x, p), p + r) - V(x, p).$$

Theorem 1 (Asymptotic stability): If a parameter-dependent Lyapunov function for (3) exists, then the origin of (3) is an asymptotically stable fixed point.
Proof: See, for example, [25, Thm. 4.1] for the CT case and [26, Thm. B.23] for the DT case.

In this paper, we consider quadratic parameter-dependent Lyapunov functions of the form

$$V(x,p) = x^\top K(p)x,$$

(7)

where the function $K : \mathcal{P} \to S^{n_x}$ is affine in $p$

$$K(p) = K_0 + \sum_{i=1}^{n_p} K_ip_i,$$

(8)

with unknown matrices $K_0, \ldots, K_{n_p} \in S^{n_x}$.

Definition 2 (Affine quadratic stability): The representation (1) is affinely quadratically stable (AQS), if it admits a parameter-dependent Lyapunov function of the form (7)-(8).

Let us provide sufficient conditions for AQS:

Theorem 2 (Sufficiency for AQS): The LPV representation (1) is affinely quadratically stable if there exist $n_p + 1$ matrices $K_0, \ldots, K_{n_p} \in S^{n_x}$ such that

$$K(p) = K_0 + \sum_{i=1}^{n_p} K_ip_i > 0,$$

(9)

for all $p \in \mathcal{P}$ and, in addition, for the CT case, it holds that

$$\mathcal{L}_c(p) = A_v(p)K(p) + K(p)A(p) + K(r) - K_0 < 0,$$

(10a)

for all $(p,r) \in \mathcal{P} \times \mathcal{V}$ or, for the DT case, it holds that

$$\mathcal{L}_d(p,r) = A_v(p)(K(p) + K(r) - K_0)A(p) - K(p) < 0,$$

(10b)

for all $(p,r) \in \mathcal{P} \times \mathcal{V}$.

Proof: For the CT case, e.g., see [3, Thm. 2.4.6]. The DT case can be obtained by similar arguments.

Theorem 2 results in an infinite set of matrix inequalities in the unknowns $K_i \in S^{n_x}$. In this paper, we convexify (10) using a partial-convexity argument to obtain a tractable solution by a finite number of LMIs. Within the IQC framework, it has been shown that relaxation by partial-convexity for systems in the form (1) lead to a less conservative formulation than a convex-hull relaxation [24, p. 9]. It is difficult to make generic statements on the potential conservativeness of various relaxation methods. However, the relaxation by partial-convexity results in less decision variables when compared to slack variable relaxation methods as discussed in [14], [16], [17]. In Section VI, we demonstrate that relaxation by partial-convexity is less conservative than slack variable relaxation. Alternatively, the uncertainty space can be partitioned as in [21], where the grid size leads to a trade-off between a conservative solution and an increased computational burden. Therefore, the partial-convexity argument potentially avoids excessive number of free parameters and decreases the number of LMIs.

IV. SUFFICIENCY FOR AQS WITH GUARANTEED CONVERGENCE

A. Relaxation with partial-convexity

The functions $\mathcal{L}_c(p,r)$ in (10a) and $\mathcal{L}_d(p,r)$ in (10b) are quadratic and cubic in $p$, respectively, while linear in $r$. Hence, a relaxation technique is required for $p$ only to obtain a finite set of LMIs to verify AQS in Theorem 2. If the functions $\mathcal{L}_c(\cdot)$ and $\mathcal{L}_d(\cdot)$ are negative definite on $(p,r) \in \mathcal{P} \times \mathcal{V}$, then the maximum of these functions must be negative. Therefore, if it can be ensured that the maximum of $\mathcal{L}_c(\cdot)$ and $\mathcal{L}_d(\cdot)$ is at the vertices $\mathcal{P}$, then (10a) and (10b) reduce to a finite set of LMIs that are required to be satisfied on $\mathcal{P}$ only. The following lemma provides the conditions for this concept:

Lemma 1 (Maximum at the vertices): Consider the cubic function $\mathcal{L} : \mathcal{P} \to \mathbb{S}$ defined by

$$\mathcal{L}(p) = Q_0 + \sum_{i=1}^{n_p} Q_i p_i + \sum_{i,j=1}^{n_p} Q_{i,j} p_i p_j + \sum_{i,j,k,l=1}^{n_p} Q_{i,j,k,l} p_i p_j p_k,$$

with matrices $Q_i, Q_{i,j}, Q_{i,j,k,l} \in \mathbb{S}$ for $i \in \tilde{\mathbb{I}}_{1}^{n_p}, j,k,l \in \tilde{\mathbb{I}}_{1}^{n_p}$. The function $L(\cdot)$ achieves its maximum at $\mathcal{P}$ if

$$\frac{1}{2} \frac{\partial^2 \mathcal{L}(u)}{\partial u_i^2} = \sum_{j=1}^{n_p} (Q_{i,j,j} + Q_{i,j,i} + Q_{i,i,j}) u_j \geq 0,$$

(11)

for all $(i,j) \in \tilde{\mathbb{I}}_{1}^{n_p} \times \mathcal{P}$ with $\mathbb{P} = \text{co}(\mathcal{P})$.

Proof: See Appendix A.

In fact, condition (11) implies that $L(\cdot)$ is a partial-convex function.

Definition 3 (Partially convex function): A twice differentiable function $L : \mathcal{P} \to \mathbb{S}$ is partially convex if $\mathcal{P}$ is convex and

$$\frac{\partial^2 L(p)}{\partial p_i^2} \succeq 0,$$

(12)

for all $(i,p) \in \tilde{\mathbb{I}}_{1}^{n_p} \times \mathcal{P}$.

Note that positive semi-definiteness of (12) is along each independent direction $p_i$ of the scheduling space. This is less demanding than convexity with respect to $p$, which would require the Hessian of $L(\cdot)$ to be positive semi-definite.

By applying the partial-convexity relaxation (11) in Lemma 1, the maximum of $\mathcal{L}_c(\cdot)$ and $\mathcal{L}_d(\cdot)$ can be found at the vertices and, therefore, the AQS test in (9)-(10) can be reduced to a finite set of LMIs at the vertices only, i.e., $\mathcal{L}_c(u,v) < 0 \forall (u,v) \in \mathcal{P} \times \mathcal{V}$. This is the core idea introduced in [11] for the CT case. This concept can also be applied in the DT case, as highlighted in Section IV-B.

By taking into account the cubic terms in $\mathcal{L}_c(\cdot)$, we differ from the approaches presented in [11]–[13]. These cubic terms are essential in handling the DT case.

B. The discrete-time case

Theorem 3 (Sufficiency for AQS in DT): Given an LPV system defined by (3) with dependency structure (2) where the scheduling variable $p(t)$ satisfies A1.

If there exists an $0 < \epsilon < 1$, such that the eigenvalues of $A(p_c)$ satisfy $|\lambda_i(A(p_c))| < \sqrt{1-\epsilon}$ with $p_c$ as in (5), and there exist $n_p + 1$ matrices $K_0, \ldots, K_{n_p} \in S^{n_x}$ parametrizing $K(\cdot)$ in (8) that satisfy

$$\mathcal{L}_d(u,v,\epsilon) = A_v^\top(u)K(u) + K(v) - K_0 A(u)$$

$$- (1 - \epsilon)K(u) \preceq 0, \quad \forall (u,v) \in \mathcal{P} \times \mathcal{V},$$

(13)

$$0 \preceq A_v^\top(u)K_1 A_1 + A_1^\top K_1 A_1(u), \quad \forall (i,u) \in \tilde{\mathbb{I}}_{1}^{n_p} \times \mathcal{P},$$

(14)

then the LPV system corresponding to (3) is AQS. In particular, $V(x,p)$ in (7) is a Lyapunov function with $\Delta V(x,p,\delta p) \leq 0$. 

In this paper, we consider quadratic parameter-dependent Lyapunov functions of the form

$$V(x,p) = x^\top K(p)x,$$
\[-cV(x, p) \text{ and the state } x \text{ robustly converges, i.e., } \|x(t)\|_2^2 \leq \frac{b}{a} (1 - \epsilon) \|x(0)\|_2^2 \text{ for any trajectory } (p(t), \delta(p(t)) \in \mathbb{P} \times \mathbb{V} \text{ for } t \geq 0 \text{ where }
\]
\[
a = \inf_{u \in \mathbb{P}} \lambda_{\min}\{\mathcal{K}(u)\}, \quad b = \sup_{u \in \mathbb{P}} \lambda_{\max}\{\mathcal{K}(u)\}. \quad (15)
\]

**Proof:** The proof has three parts: i) sufficiency of the conditions for asymptotic stability, ii) showing that \(\mathcal{K}(p) > 0\) for all \(p \in \mathbb{P}\) is implied by \(|\lambda_i(A(P_c))| < \sqrt{1 - \epsilon} \text{ together with (13)-(14) and iii) convergence of } x(t).\) Combining i) and ii) for \(0 < \epsilon < 1\) results in a parameter-dependent Lyapunov function \(V_i\) according to Theorem 2 and AQS is proven.

**Part i.** The function \(L_a(p, \delta p, \epsilon)\) in (10b) is affine in \(\delta p\) and \(\epsilon\), hence, it is sufficient to evaluate (10b) at the vertices \(V\) for an \(0 < \epsilon < 1, i.e.,\]

\[
L_a(p, v, \epsilon) < 0, \quad \forall p \in \mathbb{P}, \forall v \in \mathcal{V}, \text{ and } 0 < \epsilon < 1. \quad (16)
\]

To prove AQS, fix \(v \in \mathcal{V}\), fix \(0 < \epsilon < 1\), and define \(\mathcal{R}(v) = \mathcal{K}(v) - K_0\), then we can write (16) as

\[
L_a(p, v, \epsilon) = -(1 - \epsilon)\mathcal{K}(p) + A_0^T \mathcal{R}(v) A_0 + \sum_{i=1}^{n_p} A_i^T \mathcal{R}(v) A_i p_i + \sum_{i=1}^{n_p} A_i^T \mathcal{R}(v) A_i p_i + \sum_{i=j}^{n_p} A_i^T A_j K_i K_j A_j A_i p_i + \sum_{i=1}^{n_p} A_i^T K_0 A_0^T + \sum_{i=1}^{n_p} A_i^T K_0 A_0^T p_i
\]

\[
+ \sum_{i=1}^{n_p} (A_i^T K_0 A_0 + A_i^T K_0 A_0 + A_i^T K_0 A_0) p_i \quad (17)
\]

Based on the partial-convexity argument, Eq. (17) holds if it holds on \(\mathbb{P}\) and the following condition is satisfied

\[
\frac{\partial^2 L_a(p, v, \epsilon)}{\partial p_i^2} = 2A_i^T \mathcal{R}(v) A_i + 6A_i^T K_i A_i p_i + 2 \sum_{j=1}^{n_p} (A_i^T K_j A_i + A_i^T K_j A_i + A_i^T K_j A_i) p_j \geq 0,
\]

which can be rewritten as

\[
A_i^T [\mathcal{K}(p) + \mathcal{R}(v)] A_i + A_i^T (p) K_i A_i + A_i^T K_i A_i (p) \geq 0. \quad (18a)
\]

\[
\mathcal{A}(p) K_i A_i + \mathcal{A}(p) K_i A_i (p) \geq 0. \quad (18b)
\]

Note that the partial-convexity relaxation only requires to be positive semi-definite on the interval \(\mathbb{P}\). Also see that, \(A_i^T [\mathcal{K}(p) + \mathcal{R}(v)] A_i = A_i^T [\mathcal{K}(p+v)] A_i\), therefore, (18a) to (18b) is valid. As a consequence, the partial-convexity argument (18b) becomes independent of \(v \in \mathcal{V}\). If (18b) holds for all \((i, u) \in \mathbb{P}^n \times \mathcal{P}\) then (13) is convex on the domain \((p, r) \in \mathbb{P} \times \mathbb{V}\) and, by using Lemma 1, (13) should only be tested on the vertices of the hyper rectangle.

**Part ii.** This part will be proven by contradiction. Since \(\delta p = 0\) is admissible with \(0 < \epsilon < 1\), we write (10b) as

\[
A^T(p) K(p) A(p) - K(p) < 0. \quad (19)
\]

In addition, \(\mathbb{P}\) is compact due to A1 and, therefore, \(\mathcal{K}(p)\) is a compact function on \(\mathbb{P}\). Let us assume that \(\exists p_0 \in \mathbb{P}\) such that \(\mathcal{K}(p_0) = 0\) is singular and take \(x_0 \in \ker(K(p_0))\) with \(x_0 \neq 0\), then

\[
x^T_0 [A^T(p_0)K(p_0)A(p_0) - K(p_0)] x_0 = x^T_0 A^T(p_0)K(p_0)A(p_0)x_0 \geq 0. \quad (20)
\]

However, (20) contradicts (19), hence, (19) ensures that \(\mathcal{K}(p)\) cannot be singular for all admissible \(p \in \mathbb{P}\). As \(|\lambda_i(A(P_c))| < \sqrt{1 - \epsilon}, \mathcal{K}(p) > 0\) by the D-stability result [12]. Then, as \(\mathcal{K}(p)\) is compact on \(\mathbb{P}\), by continuity of the eigenvalues of \(\mathcal{K}(p)\), (19) assures that \(a I - \mathcal{K}(p) \geq bI\) with \(0 < a < b < +\infty\) as defined in (15) for all admissible \(p \in \mathbb{P}\) and, therefore, (9) is satisfied.

**Part iii.** We can find an \(0 < \epsilon = 1\) such that

\[
\Delta V(x, p, \delta p) + \epsilon V(x, p) = x^T [A^T(p)K(p + \delta p)A(p) - (1 - \epsilon)\mathcal{K}(p)] x = x^T L_a(p, \delta p, \epsilon) \leq 0, \quad (21)
\]

for all \((p, \delta p) \in \mathbb{P} \times \mathbb{V}\) and \(x(0) \neq 0\). Eq. (21) provides that \(V_i\) is decaying along the solutions of (3) according to \(V(x(t), p(t)) \leq (1 - \epsilon)^t V(x(0), p(0))\) for \(t > 0\). In addition, \(a|x|^2 \leq \epsilon V(x, p) \leq b|x|^2\) for all \(p \in \mathbb{P}\) and \(x \in \mathcal{X}\) since \(\mathcal{K}(p)\) is positive definite and bounded, hence, we can find that \(\|x(t)\|^2 \leq \frac{b}{(1 - \epsilon)} \|x(0)\|^2\) for \(t \geq 0\).

**Remark 1:** It is an essential part of the proof of Theorem 3 (Part i) that the function \(L_a(u)\) in (17) includes third-order terms in \(p\). In [13, Thm. 1], these terms are reduced to second-order by introducing additional variables and coupling constraints. Therefore, the proof and the LMIIs in Theorem 3 are fundamentally different from [13, Thm. 1]. Moreover, the number of decision variables in [13, Thm. 1] is twice the number of decision variables in Theorem 3.

To decrease the number of LMI conditions in Theorem 3, a more conservative test for AQS can be derived:

**Lemma 2 (Simple AQS in DT):** Given an LPV system defined by (3) with dependency structure (2) where the scheduling variable \(p(t)\) satisfies A1.

If there exist an \(0 < \epsilon < 1\) and \(n_p + 1\) matrices \(K_0, \ldots, K_{n_p} \in \mathbb{S}^{n_{\mathcal{X}_0}}\) parametrizing \(K_i\) in (8) that satisfy

\[
\mathcal{L}_1(u, l, \epsilon) = \mathcal{A}(u)K(l)u - (1 - \epsilon)K(u) < 0, \quad \forall (u, l) \in \mathcal{P} \times \mathcal{P}, \quad (22)
\]

\[
K(u) \geq 0, \quad \forall u \in \mathcal{P}, \quad (23)
\]

then the LPV system corresponding to (3) is AQS. In particular, \(V(x, p)\) in (7) is a Lyapunov function with \(\Delta V(x, p, \delta p) \leq -cV(x, p)\) and the state \(x\) robustly converges as \(\|x(t)\|^2 \leq \frac{1}{a} (1 - \epsilon)^t \|x(0)\|^2\) for any trajectory \((p(t), \delta(p(t)) \in \mathbb{P} \times \mathbb{V}\) for \(t \geq 0\) with \(a\) and \(b\) given by (15).
Robust state convergence results in AQS. Given an LPV system defined by (3) with dependency structure (2) where the scheduling variable $p(t)$ satisfies A1.

Define the following set of inequalities

$$L_k(u,v,\alpha) = \left[ \begin{array}{c} I \\ A(u) \end{array} \right]^T \left( M_k(\alpha) \otimes K(u) \right) \left[ \begin{array}{c} I \\ A(u) \end{array} \right] + Q_k(u,v), \quad \forall (u,v) \in \mathbb{P} \times \mathbb{V}$$

As (22) enforces $K(l) > 0$, (25) is satisfied. Hence, satisfying (22) and (23) results in AQS. Robust state convergence can be proven similarly to Part iii of the proof of Theorem 3 and is therefore omitted.

Note that Lemma 2 does not depend on the rate of variation $\delta p$, but we implicitly assume that $\delta p$ cannot exceed the difference between the extremes of $P$, i.e., $u_i = p_i - p_i$ and $v_i = p_i - p_i$ for $i \in \mathbb{N}_0$. This approach can only be exploited in the DT setting. The number of LMIs is decreased, however, the feasibility test is more conservative compared to Theorem 3 as the range $[u_i, v_i]$ is enlarged.

C. Generalization

Theorem 4 (AQS in CT and DT with guaranteed decay):

Given an LPV system defined by (3) with dependency structure (2) where the scheduling variable $p(t)$ satisfies A1.

Define the following set of inequalities

$$L_k(u,v,\alpha) = \left[ \begin{array}{c} I \\ A(u) \end{array} \right]^T \left(M_k(\alpha) \otimes K(u) \right) \left[ \begin{array}{c} I \\ A(u) \end{array} \right] + Q_k(u,v), \quad \forall (u,v) \in \mathbb{P} \times \mathbb{V}$$

As (22) enforces $K(l) > 0$, (25) is satisfied. Hence, satisfying (22) and (23) results in AQS. Robust state convergence can be proven similarly to Part iii of the proof of Theorem 3 and is therefore omitted.

Note that Lemma 2 does not depend on the rate of variation $\delta p$, but we implicitly assume that $\delta p$ cannot exceed the difference between the extremes of $P$, i.e., $u_i = p_i - p_i$ and $v_i = p_i - p_i$ for $i \in \mathbb{N}_0$. This approach can only be exploited in the DT setting. The number of LMIs is decreased, however, the feasibility test is more conservative compared to Theorem 3 as the range $[u_i, v_i]$ is enlarged.

V. AFFINE QUADRATIC PERFORMANCE

A. Concept of dissipativity and performance

The results on AQS of Section IV can be extended to quadratic performance measures, including $\mathcal{L}_2$ performance, positivity, and $H_\infty$ performance.

The LPV system corresponding to (1) is strictly dissipative for a given supply function $s: \mathbb{R}^{w_1} \times \mathbb{R}^{w_2} \rightarrow \mathbb{R}$ if there exist an $\varepsilon > 0$ and a storage function $V(\cdot)$ such that

$$\Delta V(x,p,\delta p) \leq s(w,z) - \varepsilon \|w\|^2, \quad \forall (w,z) \in \mathbb{R}^{w_1} \times \mathbb{R}^{w_2} \times \mathbb{R}^{w_3} \times \mathbb{R}^{w_4}$$

In other words, the change of internal storage $\Delta V(x,p,\delta p)$ will never exceed the amount of supply $s(\cdot)$ that flows into the system. The inequality (30) should be satisfied in a point-wise fashion, implying that (30) also holds for all admissible trajectories that satisfy (1). Additionally, we take $s(\cdot)$ to be the following quadratic supply function

$$s(w,z) = \left[ \begin{array}{c} w \\ z \end{array} \right]^T P \left[ \begin{array}{c} w \\ z \end{array} \right],$$

where $P \in \mathbb{S}^{w_1+w_2}$ is partitioned as $Q_s \in \mathbb{S}^{w_1}, S_s \in \mathbb{R}^{w_2 \times w_1}, R_s \in \mathbb{R}^{w_2 \times w_2}$.

B. $\mathcal{L}_2$-Gain performance

To simplify notation, we use $\mathcal{L}_2$ to indicate $L_2$ in CT and $\ell_2$ in DT.

Definition 4 (Induced $\mathcal{L}_2$-gain): Any finite $\gamma$ that satisfies

$$\sup_{0 < \|w\|_{\ell_2} < \infty} \|w\|_{\ell_2} < \gamma$$

for any trajectory $(p(t), \delta p(t)) \in \mathbb{P} \times \mathbb{V}$. Hence, $V(\cdot)$ qualifies as a quadratic storage function for $s(\cdot)$. We say that the system (1) achieves affine quadratic performance (AQP) for (31) whenever such a quadratic storage function exists.
is an $L_2$-gain upper bound where $z : T_0 \rightarrow \mathbb{R}^{n_x}$ is the response (performance variable) of (1) for $t \geq 0$ under $x_0 = 0$, general disturbance $w \in L_2(\mathbb{R}^{n_w},T_0)$ in CT or $w \in L_2(\mathbb{R}^{n_w},T_0)$ in DT, and scheduling $p \in \mathbb{P}^{n_p}$.

The $L_2$-gain performance measure of Definition 4 can be characterized by the supply function (31) by choosing $Q_s = \gamma^2 I, S_s = 0, R_s = -I$, and $\varepsilon > 0$ [27, Prop. 3.12].

Lemma 3 ($L_2$-gain performance): Given an LPV system defined by (1) with dependency structure (2) where the scheduling variable $p(t)$ satisfies A1.

If there exist a $\gamma > 0$ and $n_p + 1$ matrices $K_0, \ldots, K_{n_p} \in \mathbb{S}^{n_x}$ parametrizing $K(\gamma)$ in (8) such that

$$K(p) > 0, \quad \forall p \in \mathbb{P},$$

for all admissible $(w, p, \delta p, r, x, z)$. The choice of supply function implies the $L_2$-gain performance bound of Definition 4 based on similar arguments as in [27, Thm. 5.16].

As (33) and (34) impose an infinite number of LMIs, we make use of the partial-convexity argument to find an LMI-based test for AQP.

Theorem 5 (Sufficiency for affine $L_2$-gain performance): Given an LPV system defined by (1) with dependency structure (2) where the scheduling variable $p(t)$ satisfies A1.

Define the following set of inequalities and equalities $^2$

$$\begin{bmatrix}
L_k(p, r) & K(p) B(p) & C(p) \\
B^T(p) K(p) & -\gamma I & D^T(p) \\
C(p) & D(p) & -\gamma I
\end{bmatrix} \preceq 0, \quad \forall (p, r) \in \mathbb{P} \times \mathbb{V},$$

$$\begin{eqnarray}
N_k(u, i, \alpha) & = & 0, \quad \forall (u, i) \in \mathbb{P} \times \mathbb{V}, \\
K_i B_i & = & 0, \quad \forall i \in \mathbb{P}^{n_p},
\end{eqnarray}$$

where $L_k(\gamma)$ and $N_k(\gamma)$ are defined in (26) and (27).

For the CT case with $k = c$, if there exists an $\alpha > 0$ such that $\text{Re}(\lambda_1(A(p_c))) < -\alpha$ with $p_c$ as in (5) and there exist $n_p + 1$ matrices $K_0, \ldots, K_{n_p} \in \mathbb{S}^{n_x}$ such that (36)-(37) satisfy, then the LPV system corresponding to (1) is AQS and an $L_2$-gain performance bound $\gamma$. Moreover, $V(x, p)$ in (7) is a Lyapunov function with $\Delta V(x, p, \delta p) \leq -\alpha^2 V(x, p)$ and the state $x$ robustly converges as $\|x(t)\|^2 \leq \frac{b}{\alpha} \|x(0)\|^2$ for any trajectory $(p(t), \delta p(t)) \in \mathbb{P} \times \mathbb{V}$ for $t \geq 0$ with $w(t) = 0$ and $a, b$ given by (15).

Proof: Sufficiency for affine $L_2$-gain performance is obtained with robust state convergence if (36) holds together with the following set of inequalities:

$$\begin{bmatrix}
N_k(u, i, \alpha) & K_i B_i \\
-0 & 0 & M_{i,1}^{\top} \quad 0 & M_{i,2}^{\top} \quad \cdots \quad M_{i,p}^{\top}
\end{bmatrix} \succeq 0, \quad \forall (i, u) \in \mathbb{P}^{n_p} \times \mathbb{P},$$

where $N_k(u, i, \alpha) \in \mathbb{S}^{n_x}$ and $[M_{i,1}^{\top} \quad M_{i,2}^{\top} \quad \cdots \quad M_{i,p}^{\top}]$ is the partition of $K_i B_i$ after column and row re-arrangement with $M_{i,j} \in \mathbb{R}^{n_x \times n_n}$, $M_{i,j} \in \mathbb{R}^{n_n \times n_n \times n_n}$. Note that, in case $N_k(\alpha)$ is positive definite, $\bar{N}_k(\alpha) = \bar{N}_k(\alpha), K_i = K_i B_i$, and $M_{i,j} = 0$. Then, perform a Schur transform on (39) to obtain that (39) is equivalent to

$$\begin{bmatrix}
0 & M_{i,2}^{\top} \\
M_{i,1}^{\top} & -M_{i,1}^{\top} \bar{N}_k^{-1}(u, i, \alpha) M_{i,1}
\end{bmatrix} \succeq 0, \quad \bar{N}_k(u, i, \alpha) > 0.$$  

Then (40) implies that the blocks on the diagonal are required to be positive semi-definite, i.e., $-M_{i,1}^{\top} \bar{N}_k^{-1}(\gamma) M_{i,1} \succeq 0$. As $\bar{N}_k(\alpha)$ is positive definite, the latter condition is met if and only if:

$$M_{i,1}^{\top} \bar{N}_k^{-1}(u, i, \alpha) M_{i,1} = 0 \iff M_{i,1} = 0.$$  

Then, it follows from (40) that $M_{i,2} = 0$. Next, the matrix $K_i B_i$ can be reconstructed from elementary matrix operations based on $M_{i,1}$ and $M_{i,2}$ and we can conclude that $K_i B_i = 0$ (undo partition (39)).

To obtain the minimum of $\gamma$ satisfying (32), we solve $\min_{\gamma \geq 0} \gamma$ s.t. (36)-(37) hold. This convex optimization problem can be solved efficiently by numerical LMI solvers.

VI. NUMERICAL EXAMPLE

In this section, the AQS and AQP results are demonstrated on the mass-spring-damper system from [11] with time-invariant and time-varying parameters. For the simulation example, Matlab 2014b with Yalmip and SeDuMi3 are used. The system is discretized using a first-order approximation [28]:

$$x(t+1) = A_d(f(t), c(t)) x(t) + \begin{bmatrix} 0 \\ T_s \end{bmatrix} u(t),$$

$$A_d(k, c) = I + T_s A_c(k, c) , \quad A_c(k, c) = \begin{bmatrix} 0 & 1 \\ -k & -c \end{bmatrix},$$

$$g(t) = \begin{bmatrix} 1 & 0 \end{bmatrix} x(t).$$
where $T_s = 1/20 \text{s}$ is the sampling time and $k > 0$, $c > 0$ are the stiffness and the damping coefficients, which are assumed to be time-varying. The admissible trajectories of $k$ and $c$ are

$$k(t) = k_0(1 + p_1(t)), \quad c(t) = c_0(1 + p_2(t)),$$

(42)

where $k_0 = 1$, $c_0 = 1$, $P = [-1, 1] \times [-1, 1]$, and $\mathcal{V} = [-\delta k_{\text{max}}, \delta k_{\text{max}}] \times [-\delta c_{\text{max}}, \delta c_{\text{max}}]$. The following three experiments are performed:

1) For time-invariant $c$ ($\delta c_{\text{max}} = 0$) and time-varying $k$, the parameter box $\lambda P := \{\lambda p : p \in P\}$ is uniformly expanded with $0 < \lambda \leq 1$ to find the maximum $\lambda$ for which stability is guaranteed. This is done with respect to values of $\delta k_{\text{max}} \in [10^{-5}, 10^2]$ and $\epsilon \in [0, 1]$. The results are shown in Fig. 1.

2) For time-invariant $c$ ($\delta c_{\text{max}} = 0$) and time-varying $k$, the performance gain $\gamma$ is computed for $0.2 \mathcal{P}$. This is done w.r.t. $\delta k_{\text{max}} \in [10^{-5}, 10^2]$ and $\epsilon \in [0, 1]$. The results are shown in Fig. 2.

3) For time-varying $k$ and $c$, the parameter box $\lambda P$ is expanded to find the maximum $\lambda$ for which stability is guaranteed. This is done w.r.t. $\delta k_{\text{max}} \in [10^{-5}, 10^2]$ and $\delta c_{\text{max}} \in [10^{-4}, 10^2]$. The results are shown in Fig. 3.

Note that the case of time-invariant $k$ ($\delta k_{\text{max}} = 0$) is not considered, as it is pointed out in [11]: 'the stability region seems to be essentially determined by $\delta k_{\text{max}}$.'

Fig. 1 shows that the slack variable method [17] is indeed more conservative (in line with [17, Thm. 1]). This difference is clearly visible for small $\delta k_{\text{max}}$. For larger values of $\delta k_{\text{max}}$, the maximum parameter box size coincides with the quadratic stability test ($\delta k_{\text{max}} = \infty$), as expected. Furthermore, in the region $\delta k_{\text{max}} \in [0.03, 0.5]$, the slack variable method seems to outperform the proposed partial-convexity argument based method. Our method experiences numerical problems in the orange area for $\epsilon = 0$, see Fig. 1. In this area, neither feasibility or infeasibility can be concluded. Hence, for the proposed method, more research needs to be performed to improve numerical properties, but it is unclear if the slack variable method really outperforms the partial-convexity argument in that orange area. A similar result is also obtained for the $\mathcal{L}_2$-gain analysis in Fig. 2 (the area indicating numerical problems is not displayed in the figure).

Fig. 1 is similar to [11, Fig. 1] (CT case) in terms of the shape, as expected. However, the domain where the magnitude of $\lambda$ decreases is shifted by a factor 10, which is due to the discretization of the model. Furthermore, Fig. 3 shows that the maximum size of the parameter box is almost independent on $\delta c_{\text{max}}$, as has also been seen for the CT case [11].

**VII. CONCLUSION**

In this paper, we have proposed an LMI-based analysis for robust stability, robust state convergence, and robust performance of linear systems against uncertain and/or time-varying parameters. Affine quadratic stability is certified by finding a Lyapunov function, which is affine in the parameter. In order to get a tractable solution, the partial-convexity argument of [11] is extended for third-order terms to handle the discrete-time case. In our simulation example, the partial-convexity method really outperforms the partial-convexity argument in terms of the shape, as expected. However, the domain where the magnitude of $\lambda$ decreases is shifted by a factor 10, which is due to the discretization of the model. Furthermore, Fig. 3 shows that the maximum size of the parameter box is almost independent on $\delta c_{\text{max}}$, as has also been seen for the CT case [11].

**Figure 1:** Maximum of $\lambda$ to guarantee AQS w.r.t. $\lambda P$ under time-invariant $c$ ($\delta c_{\text{max}} = 0$) and time-varying $k$, where $\epsilon$ indicates the guaranteed rate of convergence of the state, i.e., $\|x_t\|^2 \leq \frac{b}{a}(1 - \epsilon)^t\|x_0\|^2$ for all $t > 0$. The orange area indicates numerical problems with the partial-convexity method using $\epsilon = 0$.

**Figure 2:** Minimum of the $\mathcal{L}_2$-gain performance bound $\gamma$ with time-invariant $c$ ($\delta c_{\text{max}} = 0$) and time-varying $k$. The dots indicate the last point of feasibility.

**Figure 3:** Maximum of $\lambda$ to guarantee AQS w.r.t. $\lambda P$ for a time-varying $k$ and $c$ with the partial-convexity method.
argument seems to be less conservative than the quadratic stability or the slack variable approach. For future research, the DT results can be extended to Lyapunov functions with quadratic dependence on the scheduling signal, similar to the CT case in [30]. Alternatively, the DT result can be extended to the incremental stability framework for LPV systems with bounded rates of variations [31].

REFERENCES


APPENDIX

For sufficiency, let \( p^* = (p_1^*, \ldots, p_n^*) \) be the global maximizer of \( L(\cdot) \) over \( \mathbb{P} \). Assume that \( p_i^* \) is not at a vertex of the hyper-rectangle, i.e., \( p_i < p_i^* < \bar{p}_i \), then

\[
g(p_i) = L(p_1^*, \ldots, p_{i-1}^*, p_i, p_{i+1}^*, \ldots, p_n^*) = F_{0,i} + p_i F_{1,i} + p_i^2 F_{2,i} + Q_{1,i} P_i^3,
\]

where

\[
F_{0,i} = Q_0 + \sum_{j=1}^{n} Q_j p_j^* + \sum_{j,k=1 \atop j \neq i}^{n} Q_{j,k} p_j^* p_k^* + \sum_{j,k,l=1 \atop j \neq i}^{n} Q_{j,k,l} p_j^* p_k^* p_l^*,
\]

\[
F_{1,i} = \left( Q_i + \sum_{j=1 \atop j \neq i}^{n} (Q_{j,i} + Q_{i,j}) p_j^* \right),
\]

\[
F_{2,i} = \left( Q_{i,i} + \sum_{j=1 \atop j \neq i}^{n} (Q_{j,i,i} + Q_{j,i,i}) p_j^* \right).
\]

Since \( p^* \) is the global maximizer of \( L(\cdot) \), it holds that

\[
y\top g(p_i^*) y \geq \max(y\top g(p_i) y, y\top g(\bar{p}_i) y),
\]

where \( y \neq 0 \).

On the other hand, Condition (11) imposes convexity of \( g(p_i) \) on \([p_i, \bar{p}_i] \), i.e., \( \frac{1}{p_i - \bar{p}_i} g(p_i) = F_{2,i} + 3Q_{1,i} p_i + g(\bar{p}_i) \) is implied by (11). Therefore its maximum on that interval is on the edges \( p_i^*, \bar{p}_i \). So,

\[
y\top g(p_i^*) y \leq \max(y\top g(p_i) y, y\top g(\bar{p}_i) y).
\]

Combining (44) and (45) leads to

\[
y\top g(p_i^*) y = \max(y\top g(p_i) y, y\top g(\bar{p}_i) y).
\]

Concluding, the maximum of \( L(\cdot) \) is obtained at the edges \( p_i^*, \bar{p}_i \) in case (11) is satisfied. By repeating the same argument for each \( i \) implies that the maximum of the function \( L(\cdot) \) is at a vertex of the hyper-rectangle \( \mathbb{P} \) when Condition (11) is satisfied.