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LPV Static Output Feedback for Constrained Direct Tilt Control of Narrow Tilting Vehicles

Anh-Tu Nguyen*, Member, IEEE, Philippe Chevrel, Fabien Claveau

Abstract—This paper presents a new direct tilt control (DTC) design to improve the lateral stability and the driving comfort of narrow tilting vehicles. To this end, a conceptual model is constructed from the vehicle dynamics, a simplified model of the driving environment, and the vehicle perceived acceleration. This latter is considered as the main performance variable of the related \(H_2\) control problem. The conceptual model is then represented in a polytopic form, which is the basis of a linear parameter-varying (LPV) form for control purposes. To avoid the use of costly vehicle sensors while favoring the simplest control structure for real-time implementation, a new LPV static output feedback (SOF) control method is proposed. Thanks to Lyapunov stability arguments, physical constraints on both system states and DTC actuator are explicitly considered in the design procedure to improve the safety and the comfort of passengers. Moreover, a parameter-dependent Lyapunov function is exploited for theoretical developments. In this way, the finite bounds on vehicle speed and acceleration are effectively taken into account in the control design to reduce the conservatism. The \(H_2\) control design is recast as an LMI-based optimization which can be easily solved with numerical solvers. The resulting robust DTC controller is evaluated with realistic driving scenarios.

Index Terms—Narrow tilting vehicles, direct tilt control, static output feedback control, LPV control, vehicle dynamics, linear matrix inequality (LMI).

I. INTRODUCTION

Narrow tilting vehicles (NTVs) have been increasingly studied as a promising solution to traffic congestion, pollution, and parking issues in urban areas [1]–[5]. Moreover, the reduced dimensions of NTVs also result in their high fuel efficiency [3], [4]. Due to their special features, NTVs are characterized by a high center of gravity (c.g.) leading to the major issue on roll stability [6]–[8]. Indeed, to maintain the vehicle stability, NTVs should lean while cornering as motorcycles to compensate the effects of the centrifugal force. Hence, effective tilt control systems are essential elements in any narrow vehicle system design, which greatly improves the acceptability of NTVs with respect to standard vehicles [7]. Up to now, a few NTV prototypes have been developed in the automotive industry, e.g., F-300 Life Jet by Mercedes-Benz (1997), Brink Dynamics by Carver (2003), SMERA by Lumeneo (2008), Land Glider by Nissan (2009), see [3], [9] for more details.

Two main types of control systems are available for vehicle tilting [7]: direct tilt control (DTC), and steering tilt control (STC). STC relies on a steering actuator to control the vehicle tilt in the same way as a moto rider [10]. This control strategy has some drawbacks: (i) it is not suitable at low speeds, nor on slippery roads [3], (ii) it may require a large countersteering to tilt the vehicle which leads to a significant trajectory deviation and ride discomfort [10]. Using a dedicated tilt actuator, DTC strategy can directly control the vehicle roll. Then, DTC could be used to address the major drawbacks of STC. However, the main drawback of DTC consists in its energy consumption and discomfort at the beginning of curve taking [6]. It has been shown that the integrated approach, i.e., the combination of STC and DTC, can lead to the best control performance [3], [11].

Unfortunately, this solution requires both a tilt actuator and a steer-by-wire system, which increases the cost of NTVs [10].

This work is the continuity of our collaboration with Lumeneo company in developing control strategies for the SMERA vehicle [6], [9]. This four-wheeled NTV has two seats in tandem and an DTC actuator for tilt control, see Fig. 1. As in our previous studies [6], a direct regulation/minimization of the perceived acceleration will be considered for the control design. This allows avoiding both the online computational complexity and the residual tilt torque, thus saving the energy consumption. The latter is caused by approximation errors of the tilt angle reference in tracking control approaches largely discussed in the literature, see [1]–[3], [5], [8], [11], [13] and references therein. Note that most of DTC methods have considered a constant vehicle speed to ease the design task, see [6], [10] for short surveys. However, the corresponding linear controllers cannot provide a satisfactory closed-loop performance under various driving circumstances [14]. Moreover, these methods are usually based on a state feedback control scheme which requires full vehicle sensor information for real-time implementation. This paper presents a systematic DTC method which can effectively address the above technical and practical control issues. The main contributions can be summarized as follows.

- Using an SOF control scheme, the proposed DTC controller is easily realized from engineering viewpoint without needing an important vehicle sensor to measure the lateral speed. Differently from [6], the new control method does not require any online estimation of the vehicle states which can lead to online computational burden, approximation errors, and especially an algebraic loop for real-time implementation. Moreover, similar to [6], the new method can be easily adapted to STC and integrated control approaches.

- LPV paradigm has been demonstrated as an effective tool for modeling and control in a variety of engineering applications, see [15]–[17] and related references. Here, the time-varying nature of the vehicle speed is tackled with a novel LPV control framework. Especially, the finite bounds on both vehicle speed and acceleration are explicitly considered in the \(H_2\) control via a parameter-dependent Lyapunov function to reduce the design conservatism.

- The new DTC method can explicitly take into account the physical constraints on both the tilt torque and the system states in the \(H_2\) control procedure to improve not only the energy consumption of DTC actuator but also the safety and the comfort of passengers. This major issue for lateral control of NTVs has not been well addressed in the open literature [8]. The closed-loop performance of the LPV vehicle system is theoretically proved using Lyapunov stability theory, which is not the case of most existing methods [6]. In particular, the design conditions are formulated as an LMI optimization which can be effectively solved with numerical solvers [18]. Note that LMI-based \(H_2\) static output control for LPV systems still remains an open research topic [19]. The proposed theoretical results go beyond the scope of the considered application and can be applied to a larger class of LPV systems.

The paper is organized as follows. Section II presents the nonlinear model of NTVs used for simulation purposes and formulates the control goals. In Section III, we define an LPV standard model of NTVs used for lateral control purposes. Section IV presents a new robust SOF method allowing to achieve several control specifications.
of NTVs. The effectiveness of the new DTC method is demonstrated in Section V. Conclusions are given in Section VI.

Notation. \( \Omega_N \) denotes the number set \( \{1, 2, \ldots, N \} \). I denotes the identity matrix of appropriate dimension. For a matrix \( X, X^\top \) indicates its transpose, and \( X_{(i)} \) denotes its \( i \)th row. The \( i \)th element of a vector \( u \) is denoted by \( u_i \), and \( \ast \) stands for matrix blocks deduced by symmetry. \( \text{co}[S] \) denotes the convex hull of the set \( S \). The time argument is dropped when convenient.

II. VEHICLE MODELING AND PROBLEM DEFINITION

Several models of NTVs have been proposed for both simulation and control purposes, see for instance [7], [9], [12], [20], [21]. This section presents the nonlinear model of the SMERA vehicle used for our simulation study. Then, the related control problem is formulated.

The vehicle nomenclature is given in Table I.

A. Nonlinear Model of Narrow Commuter Vehicles

Fig. 2 depicts the four degrees of freedom (DOF) of the SMERA vehicle: the longitudinal and lateral positions \((x, y)\) of the vehicle, the tilt angle \(\theta\), and the yaw angle \(\psi\). The corresponding dynamics model was developed in collaboration with Lumeni company by inspiring from two nonlinear vehicle models. The first one focusses on the dynamics of the vehicle lateral position \(y\), the tilt angle \(\theta\), and the vehicle yaw \(\psi\) while considering a constant vehicle speed [7].

The second bicycle model represents both lateral and longitudinal dynamics [22]. Then, the SMERA dynamics is described by

\[
\begin{align*}
\dot{\mathbf{v}}_x & = F_{Ff} \sin(\beta + \delta) + F_{Ff} \cos(\beta - \delta) + F_{Fr} \sin(\beta - \delta) \cos \beta \sin \beta \\
\dot{\mathbf{v}}_y & = F_{Ff} \cos(\beta - \delta) - F_{Ff} \sin(\beta + \delta) - F_{Fr} \cos \beta \sin \beta \\
\dot{\theta} & = l_f (F_{Ff} \cos \beta + F_{Fr} \sin \beta) - l_r, F_{Fr} \\
\dot{\psi} & = \frac{mh}{\mathbf{I}_{xx}} \sin \theta - mh^2 \dot{\psi} \cos \theta \sin \theta - mh^2 \dot{\theta} \sin^2 \theta \\
\dot{\mathbf{v}}_x & = F_{Ff} \cos \beta \sin \beta + \mathbf{I}_{xx} \dot{\theta} + M_t 
\end{align*}
\]

where \( F_{Ff} \) gives the front/rear tire forces, \( \mathbf{I}_{xx} \) is the tilting/yaw moment of inertia of the vehicle, \( M_t \) is the total moment of inertia of the vehicle, \( \mathbf{I}_{xx} \) is the elastic modulus of the vehicle, \( h \) is the height of the vehicle, and \( m \) is the mass of the vehicle.

B. Available Sensors for Real-Time Control Implementation

As most of NTVs, SMERA is equipped with a tilt angle sensor and an inertial measurement unit (IMU), which provide the measurements of the vehicle states \(\theta, \dot{\theta}\), and \(\psi\). An accelerometer is used to measure the vehicle speed \(v_x\) whereas the steering angle \(\delta\) and its derivative \(\dot{\delta}\) are obtained from an optical encoder. The IMU provides also the lateral acceleration \(a_{per}\) at the gravity center \(G\), defined as follows [7]:

\[
a_{per} = (v_x + v_y \dot{\psi}) \cos \theta + h \dot{\theta} - g \sin \theta
\]

The acceleration \(a_{per}\) plays a crucial role in the study of lateral stability of NTVs, and the comfort of passengers [6]–[8].

The sideslip angle \(\beta\) and the lateral speed \(v_y\) can be measured by a CORREVIT sensor. Unfortunately, due to the excessive cost of this optical sensor (about 15k€ per unit), the measurements of \( \beta \) and \( v_y \) are unavailable for control implementation [24]. This paper presents a systematic method for multi-objective lateral control of NTVs modeled by (1) which can handle this major practical issue.

C. Problem Statement and Control Goals

Automatic DTC controllers aim to guarantee the lateral stability of NTVs, i.e., to regulate the perceived acceleration \(a_{per}\) around zero during cornering [3]. Here, the following specifications are required for DTC control design.

- DTC controllers should be easily computed and implemented with only available vehicle sensors. The closed-loop control performance and robustness can be demonstrated using Lyapunov stability arguments.
- The integral of the perceived acceleration \(a_{per}\), denoted by \(a_{per}^I\), should be directly regulated and minimized to: (i) avoid static errors during long curves, (ii) improve the comfort of passengers and the energy consumption [6].
- The constraints on both the system states and the tilt actuator should be explicitly taken into account in the control design to improve both the safety and the comfort of passengers.
To meet these specifications, we propose in Section IV a new LPV-based SOF control method in multiobjective setting.

III. STANDARD MODEL FORMULATION FOR $H_2$ CONTROL

Based on an $H_2$ control scheme, the proposed DTC method makes use of a standard model $Σ$ composed of three generic elements: plant model $Σ_p$, environment model $Σ_w$, and model of regulated signals $Σ_e$, see Fig. 3. Next, these three elements are first defined in the similar way as in [6]. Then, we construct the corresponding control-based LPV standard model.

![Standard Model](image)

Fig. 3. Structure of the standard model $Σ$ used for $H_2$ control design.

A. Vehicle Plant Model

For lateral control purposes, a 3 DOF vehicle model is derived from (1). To this end, the following usual assumptions are considered [7]. (i) The longitudinal dynamics is neglected. (ii) The lateral tire forces are proportional to the slip angles of each axle. (iii) The vehicle angles are small. It is important to note that these assumptions are relevant for normal driving conditions in urban areas which are the control focus of this paper. Then, the lateral dynamics of NTVs can be modeled as follows [8]:

$$Σ_p : \dot{x}_p = A_p x_p + B_p u + B_p δ \tag{4}$$

where $x_p = \begin{bmatrix} y_p & \psi & θ & \dot{θ} \end{bmatrix}^T$ is the vehicle state vector, and the control input is the tilt torque from the DTC actuator $u = M_1$. The system matrices of (4) are given by

$$A_p = \begin{bmatrix} a_{11} & a_{12} & a_{13} & 0 \\ a_{21} & a_{22} & a_{23} & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & 0 \end{bmatrix}, \quad B_p u = \begin{bmatrix} \frac{b}{I_x} \\ 0 \\ 0 \\ \frac{2C_f}{I_x} \end{bmatrix},$$

and

$$B_p = \begin{bmatrix} 2C_f \left( \frac{b}{I_x} + \frac{b_y}{I_y} \right) & -2C_f \frac{b_y}{I_y} & 0 & -2C_f \frac{b_y}{I_y} \end{bmatrix}^T,$$

where

$$a_{11} = -\frac{1}{I_x} \left( \frac{b}{I_x} + \frac{b_y}{I_y} \right), \quad a_{12} = -\frac{1}{I_x} \left( \frac{b}{I_x} + \frac{b_y}{I_y} \right) - v_x,$$

$$a_{13} = 2(\lambda_f + \lambda_r) \left( \frac{1}{I_m} + \frac{b^2}{I_x} \right) - \frac{mg^2}{I_x}, \quad a_{21} = -\frac{b}{I_x v_x},$$

$$a_{22} = -2(\frac{C_f + \lambda_f}{I_x}), \quad a_{23} = 2(\frac{I_y}{I_x} \lambda_f - \lambda_r),$$

$$a_{31} = \frac{b}{I_y}, \quad a_{32} = \frac{b_y}{I_y}, \quad a_{33} = \frac{mg^2}{I_x} - 2(\lambda_f + \lambda_r),$$

$$a = 2(C_f + C_r), \quad b = 2(C_f \lambda_f - C_r \lambda_r).$$

The output equation of system (4) is given by

$$y_p = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} x_p = C_p y_p.$$

B. Environment Model

The goal is to stabilize the lateral acceleration $a_{per}$ under the variation of the steering actions. Hence, the environment model of $Σ_p$ represents the a priori knowledge available on $δ$. The following model is used for the curved trajectory prediction [6]:

$$Σ_w : \begin{cases} \dot{x}_w = A_w x_w + B_{1w} w \\ y_{1w} = C_{1w} x_w, \quad y_{2w} = C_{2w} x_w \end{cases} \tag{5}$$

with $x_w = [δ \, \dot{δ}]^T$, $w$ is an impulse signal and

$$A_w = \begin{bmatrix} 0 & 1 \\ -α_1α_2 & -(α_1 + α_2) \end{bmatrix}, \quad C_{2w} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},$$

$$B_{1w} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad C_{1w} = \begin{bmatrix} 1 \\ 0 \end{bmatrix},$$

where $A_w$ is Hurwitz with $α_1 = 0.5$ and $α_2 = 1$. The following remark is reported for the environment model $Σ_w$.

**Remark 1.** The environment model (5) represents the fact that the steering angle $δ$ is band limited and can be truncated in sequences of asymptotically convergent signals. Note that the time constant of $Σ_w$ is about $2s$ which is reasonable for road curvature prediction in most real-world situations. This cannot be considered as a driver model since its dynamics does not depend on that of the vehicle. However, the consideration of such a predictor model in the control design offers a significant performance improvement. Especially, for the case of NTVs, the introduction of $δ$ in the output $y_{2w}$ of $Σ_w$ improves the prediction capacity of DTC controller with respect to curved trajectories to avoid an excessive tilt torque [6].

C. Model of Regulated Signals

As stated above, the integral of $a_{per}$ should be directly controlled and minimized to improve the DTC performance. The model of the regulated signal $a_{per}^{\dot{}}$ is given by

$$a_{per}^{\dot{}} = a_{per} \tag{6}$$

From (3), model (6) can be represented in the following form by considering the small angles assumption:

$$a_{per}^{\dot{}} = a_{per} \approx \dot{v}_y + v_x \dot{ψ} + h \dot{θ} - g \dot{θ} \tag{7}$$

where $G_1 = [0 \ v_x \ -g \ 0]$ and $G_2 = [1 \ 0 \ 0 \ h]$. Moreover, following the guideline in [25], the performance vector $z$ associated to model (7) can be chosen as follows:

$$z = W_e(s)a_{per}, \quad W_e(s) = \frac{κs + M}{M_K} \tag{8}$$

where the parameters $M$ and $κ$ are positive. The weighting function $W_e(s)$ is defined as above for two reasons. First, this guarantees that $a_{per}$ should be less than $M$ in magnitude at high frequencies. Second, we integrate an integral action and require a response time better than about $κ$.

From (6), (7) and (8), the model $Σ_e$ can be represented as

$$Σ_e : \begin{cases} \dot{x}_e = A_e x_e + B_e x_p + B_e w x_w \\ z = D_ex_p + D_e x_e + D_e w x_w, \quad y_e = C_e x_e \end{cases} \tag{9}$$

where $x_e = a_{per}^{\dot{}}$ and

$$A_e = \begin{bmatrix} 0 \\ B_e x_p \\ B_e x_e \end{bmatrix}, \quad B_e = [1 \ 1 \ 0], \quad C_e = 1.$$
Remark 2. Note that the dynamics matrix and the performance matrix of the standard model $\Sigma(v_x)$ depend explicitly on the time-varying speed which is measured and bounded

\[ v_{\min} \leq v_x \leq v_{\max}, \quad v_{\min} = 2 \, [m/s], \quad v_{\max} = 18 \, [m/s] \quad (11) \]

Different methods using different LPV representations, e.g., linear fractional transformation (LFT) form, polytopic descriptor form, etc. [17], can be applied for the control design of LPV system (10). However, a polytopic LPV formulation has been chosen here since it leads to a simple characterization of the LPV controller for NTVs. As shown later, the proposed control solution is also of reasonable complexity for real-time implementation.

There are two dependently varying parameters involved in the dynamics of LPV system (10), i.e., $\omega(t) = \left[ v_x \quad \frac{1}{v_x} \right]^T$. These parameters form a convex hull $P_{\omega}$ with four vertices

\[
\omega_{v1} = \left[ \frac{v_{\min}}{v_{\min}} \right]^T, \quad \omega_{v2} = \left[ \frac{v_{\max}}{v_{\max}} \right]^T, \\
\omega_{v3} = \left[ \frac{v_{\min}}{v_{\min}} \right]^T, \quad \omega_{v4} = \left[ \frac{v_{\max}}{v_{\max}} \right]^T.
\]

Observe in Fig. 4 that the parameter polytope $P_{\omega}$ with four vertices leads to a simple characterization of the LPV controller for NTVs. However, a polytopic LPV formulation has been chosen here since it leads to a simple characterization of the LPV controller for NTVs.

It is easy to verify that $v_x = v_{\min}$ for $\omega = \omega_{\min}$ and $v_x = v_{\max}$ for $\omega = \omega_{\max}$. Hence, $\omega$ can be used to describe the variation of $v_x$ between its lower and upper bounds. Moreover, using the Taylor’s approximation as in [26], the vehicle speed can be approximated from the second expression in (12) by $v_x \approx \frac{v_0}{1 - \eta \omega}$. As a consequence, the parameter curve $C_{\omega}$ is approximated by the straight line $C$, see Fig. 4. Remark that the expressions of both $v_x$ and $1/v_x$ are now linearly dependent on $\omega$. Substituting these expressions into (10), it can be easily observed that the corresponding standard model of the SMERA vehicle

\[
\Sigma(\omega) : \left\{ \begin{array}{l}
\dot{x} = A(\omega)x + B_u u + B_o w \\
z = C_x(\omega)x, \quad y = C_y x 
\end{array} \right.
\]

depends linearly on the new time-varying parameter $\omega$. Using the sector nonlinearity approach [27, Chapter 2], $\Sigma(\omega)$ defined in (14) can be exactly represented in the polytopic LPV form

\[
\Sigma(\omega) : \left\{ \begin{array}{l}
\dot{x} = \sum_{i=1}^{2} \eta_i(\omega)(A_i x + B_i^u u + B_i^w w) \\
z = \sum_{i=1}^{2} \eta_i(\omega)C_i^x x, \quad y = C_y x 
\end{array} \right.
\]

where the membership functions (MFs), also called barycentric coordinates, and the state-space matrices are given by

\[
\eta_i(\omega) = \frac{1 - \omega_i}{2}, \quad \eta_i(\omega) = \frac{1 - \eta_i(\omega)}, \quad A_i = A(\omega_i), \quad B_i^u = B_i^u, \quad B_i^w = B_i^w, \quad B_i = B_i, \\
A_2 = A(\omega_{\max}), \quad C_i^x = C_i(\omega_i), \quad C_i^y = C_i(\omega_{\max}).
\]

It is clear now that using the variable change (12) together with the above Taylor’s approximation, the number of vertices is reduced from four to two. From the practical viewpoint, note that the induced approximation error is expected to be small over the whole system (10) since only a part of the element $a_{12}$ of matrix $A_p$ in (4) is affected by this approximation. This is also justified by experimental results on vehicle control presented in [26].

Remark 3. Besides the bounds on the vehicle speed (11), those of the vehicle acceleration $a_v = \dot{v}_x$ are also given

\[
amin \leq a_v \leq amax, \quad amax = -amin = 3.5 \, [m/s^2] \quad (16)
\]

These physical acceleration bounds allow to limit the theoretical kinematic centripetal acceleration of the vehicle [14]. From (12) and (16), it follows that

\[
amin \leq \omega \leq amax, \quad a_0 = \frac{-v_0^2}{v_1} \quad (17)
\]

As proved later, an explicit consideration of the bounds on both vehicle speed and acceleration via (13) and (17) in the control design allows reducing further the design conservatism.

IV. LPV MULTIOBJECTIVE STATIC OUTPUT CONTROL

This section presents new conditions to design a multiobjective SOF controller that will be used for the SMERA vehicle.

A. Preliminaries

Let us consider LPV system (15) in the general form

\[
\dot{x} = \sum_{i=1}^{N} \eta_i(\omega)(A_i x + B_i^w u + B_i^w w) \\
z = \sum_{i=1}^{N} \eta_i(\omega)(C_i^x x + D_i^w u), \quad y = C_y x 
\]

where $x \in \mathbb{R}^{n_x}$ is the state, $u \in \mathbb{R}^{n_u}$ is the control input, $w \in \mathbb{R}^{n_w}$ is the disturbance, $x \in \mathbb{R}^{n_x}$ is the performance output, and $y \in \mathbb{R}^{n_y}$ is the system output. The scheduling vector $\omega \in \mathbb{R}_+^n$ is measured and assumed to be confined to a compact set $P_{\omega} \subset \mathbb{R}^n$, defined by the following convex hull:

\[
P_{\omega} = \{ \omega \in \mathbb{R}_+^n \mid \omega_i \leq \omega_i \leq \omega_i \}, \quad i \in \Omega, \quad N \]

where the vertices $\omega_i, i \in \Omega$, are determined by all combinations of the upper and lower bounds $\omega_{\min}$ and $\omega_{\max}$ of individual scheduling parameters. The constant matrices $A_i, B_i^w, B_i^w, C_i^x, C_y, i \in \Omega, N$, are of adequate dimensions. The MFs in (18) satisfy the property

\[
\sum_{i=1}^{N} \eta_i(\omega) = 1, \quad \sum_{i=1}^{N} \eta_i(\omega) = 0 
\]

where $\phi_1 \leq \phi_2 \,$ are known lower and upper bounds of $\eta_i(\omega)$.
Remark 4. Given the bounds of $\omega$ and its rate of variation $\dot{\omega}$, the values of $\phi_{11}$ and $\phi_{22}$, for $i \in \Omega_N$, can be easily obtained, e.g., it follows from (13) and (17) that
\[
\phi_{11} \leq \dot{\eta}_1(\omega) \leq \phi_{12}, \quad \phi_{21} \leq \dot{\eta}_2(\omega) \leq \phi_{22},
\]
where
\[
\phi_{11} = -\frac{a_{\text{max}}}{2g_0}, \quad \phi_{12} = -\frac{a_{\text{min}}}{2g_0}, \quad \phi_{21} = \frac{a_{\text{min}}}{2g_0}, \quad \phi_{22} = \frac{a_{\text{max}}}{2g_0}.
\]
We consider the parameter-dependent SOF controller
\[
\mathbf{u} = \sum_{i=1}^{N} \eta_i(\omega) \mathbf{K}_i \mathbf{y} = \mathbf{K}(\omega) \mathbf{y}
\]
(21)
From (18) and (21), the closed-loop system is rewritten as
\[
\begin{align*}
\Sigma_{cl}(\omega) : & \quad \dot{x} = \hat{A}(\omega)x + B_u(\omega)w, \\
& \quad \dot{z} = \hat{C}_z(\omega)x
\end{align*}
\]
where
\[
\hat{A}(\omega) = A(\omega) + B_u(\omega)K(\omega)C_y, \quad \hat{C}_z(\omega) = C_z(\omega) + D_z(\omega)K(\omega)C_y.
\]
This paper proposes a constructive solution for the following control problem.

Problem 1. Determine the parameter-dependent matrix gain $K(\omega)$ such that the SOF controller (21) stabilizes LPV system (18) while minimizing the $H_2$ norm $\|\Sigma_{cl}(\omega)\|_2$ of the closed-loop system (22) with $\omega \in \mathcal{P}_\omega$, $\forall t > 0$, and the compact set $\mathcal{P}_\omega$ is defined in (19).

Note that the $H_2$ control performance is considered to achieve a robust regulation of the lateral acceleration $a_{\text{per}}$ under the variation of the steering actions. Hence, this allows improving the DTC performance of the SMERA vehicle during bending taking. For stability analysis and control design, we consider the following parameter-dependent Lyapunov function (PDLF):
\[
V(x) = x^T \left( \sum_{i=1}^{N} \eta_i(\omega)Q_i \right)^{-1} x = x^T Q(x)^{-1} x
\]
where $Q_i > 0$, for $\forall i \in \Omega_N$. The following result is standard in the $H_2$ control framework, see for example [28].

Lemma 1. Consider LPV system $\Sigma_{cl}(\omega)$ in (22) with $\omega \in \mathcal{P}_\omega$, $\forall t > 0$. If there exist a positive definite matrix $Q(\omega) \in \mathbb{R}^{n_x \times n_x}$, a matrix $Z(\omega) \in \mathbb{R}^{n_u \times n_x}$, and a positive scalar $\gamma$ such that
\[
\begin{bmatrix}
\text{He}(\hat{A}(\omega)Q(\omega) - \dot{Q}(\omega) * ) & -I \\
Z(\omega) & B_u(\omega)Q(\omega)
\end{bmatrix} < 0
\]
and
\[
\text{trace}(Z(\omega)) < \gamma^2
\]
Then it follows that $\|\Sigma_{cl}(\omega)\|_2 < \gamma$ and the associate Lyapunov function of LPV system (22) is given in (23).

Remark 5. The design conditions in Lemma 1 depend explicitly on both $\omega$ and $\dot{\omega}$ (via the term $\dot{Q}(\omega)$). Moreover, the control gain $K(\omega)$ appears nonlinearly in the expressions of $\hat{A}(\omega)$ and $\hat{C}_z(\omega)$ in (22). Hence, it is not trivial to obtain an effective solution from such conditions. On the basis of Lemma 1, we propose hereafter new tractable conditions to design an SOF controller (21).

In the framework of polytopic systems, many control design conditions can be represented in the following form [29]:
\[
\Upsilon(\omega) = \sum_{i=1}^{N} \sum_{j=1}^{N} \eta_i(\omega)\eta_j(\omega)\Upsilon_{ij} < 0
\]
where matrices $\Upsilon_{ij}$ are linearly dependent on the decision variables and $\omega \in \mathcal{P}_\omega$. To convert the parameter-dependent condition (27) into a finite set of LMIs while avoiding excessive computational burden of parameter-gridding algorithms, the MFs have to be dropped out. Without involving slack variables, the following lemma leads to a good tradeoff between numerical complexity and conservatism [30].

Lemma 2. Let $\Upsilon_{ij}, i, j \in \Omega_N$, be symmetric matrices of appropriate dimensions, and $\{\eta_i\}_{i \in \Omega_N}$ be a family of functions satisfying (20). Condition (27) holds if
\[
\Upsilon_{ii} < 0, \quad \frac{2}{N-1} \Upsilon_{ii} + \Upsilon_{ij} + \Upsilon_{ji} < 0
\]
for $i, j \in \Omega_N$, and $i < j$.

Using slack variables, relaxation results with different degrees of design conservatism and/or computational complexity can be found in [29].

B. LMI-Based $H_2$ Static Output Feedback Control

The following theorem provides LMI-based conditions to design an $H_2$ SOF controller (21) for LPV system (18).

Theorem 1. Given an LPV system (18) with $\omega \in \mathcal{P}_\omega$, $\forall t > 0$. If there exist symmetric positive definite matrices $\Omega_i, i \in \Omega_N$, matrices $M_i \in \mathbb{R}^{n_u \times n_x}$, matrices $Z_i \in \mathbb{R}^{n_u \times n_x}$, for $i \in \Omega_N$, and positive scalars $\epsilon, \gamma$ satisfying the following optimization:
\[
\text{minimize} \quad \gamma^2
\]
subject to
\[
\begin{bmatrix}
Z_i & * \\
B_u^T & Q_i
\end{bmatrix} > 0
\]
trace($Z_i$) $< \gamma^2$
\[
\Phi_{ijklm}^{klm} < \frac{2}{N-1} \Phi_{lijk}^{klm} + \Phi_{ijkl}^{klm} + \Phi_{ijklm}^{klm} < 0
\]
for $i, j, k, l \in \Omega_N$, $i < j, k \neq l$, and $m \in \Omega_2$. The quantity $\Phi_{ijklm}^{klm}$ is defined as follows:
\[
\Phi_{ijklm}^{klm} = \text{He}
\]
\[
D_i^T M_j C_l + C_i^T Q_j \quad 0 \quad \epsilon B_i^T M_j
\]
\[
C_l^T Q_j - X C_i \quad 0 \quad -\epsilon X
\]
with $\Phi_{ijklm}^{klm} = A_i Q_j + B_i^T M_j C_l - \phi_{klm}(Q_j - Q_i)$./2. Then, the SOF controller (21) solves Problem 1. Moreover, the control feedback gains in (21) are given by
\[
K_i = M_i X_i^{-1}, \quad i \in \Omega_N
\]
Proof. Multiplying (29) by $\eta_i(\omega)$ and summing up for all $i \in \Omega_N$, we obtain (25). In the same fashion, (30) implies (26). Note from the definition of $\Phi_{ijklm}^{klm}$ in (32) that if (31) holds, it follows that $X + X^T > 0$. This guarantees the nonsingularity of $X$, thus the validity of the gain expression in (33).

Exploiting the constraint $\sum_{i=1}^{N} \dot{\eta}_i(\omega) = 0$ in (20), it can be easily deduced that
\[
\dot{Q}(\omega) = \dot{\eta}_i(\omega)Q_i + \sum_{k \neq i} \dot{\eta}_k(\omega)Q_k = \sum_{k \neq i} \dot{\eta}_k(\omega)(Q_k - Q_i)
\]
For any $\phi_{k1} \leq \dot{\eta}_k(\omega) \leq \phi_{k2}$, we can rewrite
\[
\dot{\eta}_k(\omega) = \chi_k(\omega) \phi_{k1} + \chi_k(\omega) \phi_{k2}, \quad k \in \Omega_N
\]
where
\[
\chi_k(\omega) = \phi_{k2} - \dot{\eta}_k(\omega), \quad \chi_k(\omega) = \dot{\eta}_k(\omega) - \phi_{k1}.
\]
Note that $\chi_k(\omega) \geq 0$, $\sum_{i=1}^{N} \chi_k(\omega) = 1$, for $k \in \Omega_N$. From (34) and (35), $\dot{Q}(\omega)$ can be exactly represented as follows:
\[
\dot{Q}(\omega) = \sum_{k \neq i} \sum_{m=1}^{N} \chi_m(\omega) \phi_{km}(Q_k - Q_i)
\]
Using expressions (32) and (36), condition (31) can be equivalently represented by (28), where

\[
\begin{bmatrix}
Y_{11}(\omega)
\end{bmatrix}
= \begin{bmatrix}
0 \\
D_\Omega^g M_j C_\Omega + C_\Omega^g Q_j \\
C_\Omega Q_j - X C_\Omega
\end{bmatrix} \\
0 \\
\epsilon Z_d^g M_j
\]

and \( Y_{11}(\omega) = A_i Q_i + B_i^g M_j C_\Omega - Q(\omega)/2 \). By Lemma 2, condition (28) implies clearly that

\[
Y(\omega) = \begin{bmatrix}
Y_{11}(\omega) \\
Y_{21}(\omega)
\end{bmatrix}
= \begin{bmatrix}
0 \\
-1/2 \\
0
\end{bmatrix}
\]

where \( Y_{11}(\omega) = A(\omega) Q(\omega) + B_n(\omega) M(\omega) C_\Omega - Q(\omega)/2, \) \( Y_{21}(\omega) = D_\Omega M(\omega) C_\Omega + C_\Omega(\omega) Q(\omega) \) and \( Y_{21}(\omega) = C_\Omega Q(\omega) - X C_\Omega, \) Pre- and postmultiplying (37) \( \times \) \[ 0 \quad B_n(\omega) M(\omega) X^{-1} \]
and its transpose, we obtain (24) after some simple but tedious algebraic manipulations. By Lemma 1, the proof of Theorem 1 can be now concluded.

**Remark 6.** The information on both \( \omega \) and \( \xi \) is explicitly considered in the control design by exploiting the bounds \( \phi_{\xi}, k \in \Omega_x, l \in \Omega_\xi, \) see Remark 4. This allows using the PDLF (23) to reduce the design conservatism. Indeed, if condition (31) is feasible for arbitrarily high variation of the MFs, \( \xi \approx \infty \) and \( \phi \approx +\infty, \forall k \in \Omega_x, \) then the only possible solution is \( Q_l \approx \cdots \approx Q_N \to \) to minimize the effects of \( \phi_{\xi}(Q_k - Q_k) \) involved in (32). On the other hand, if one imposes that \( Q_l = Q, \forall \in \Omega_x, \) in (23), then the common quadratic Lyapunov function \( V(x) = x^T Q^{-1} x \) is recovered. This discussion shows that the result of Theorem 1 includes precisely that of quadratic approaches. A similar conclusion for the case of state-feedback control of affine LPV systems can be found in [28], [31].

### C. Constraints on Control Input and System States

It has been shown that even the NTV is at an equilibrium in a perfectly coordinated turn, i.e., only a small amount of torque is required for small deviations, tilting the vehicle into a turn at high speeds may require excessive torque values [8]. Hence, to improve the energy consumption of the tilt actuator and also the ride qualities, the amplitude-limitation \( |u(t)| \leq \bar{u}, \forall t \geq 0, \) where \( \bar{u} \) is the actuator saturation level, should be imposed for control design. Moreover, as shown in [26] and in the sequel, many safety and comfort criteria can be mathematically translated into state constraints of the form

\[
x \in D_x = \{ x \in \mathbb{R}^{n_x} : |H(\Omega_m)x| \leq 1, \ m \in \Omega_x \}
\]

where the given matrix \( H \in \mathbb{R}^{n_x \times n_x} \) characterizes the state domain \( D_x \). Hence, taking into account explicitly the state constraints (38) in the control design is crucial to improve both the safety and the comfort of passengers. Such design constraints can be represented in terms of matrix inequalities as shown in the following theorem.

**Theorem 2.** Given an LPV system (18) with \( \omega \in \Omega_x, \forall t \geq 0, \) and \( |x(0)| \leq \phi, \) for \( \phi > 0. \) If there exist symmetric positive definite matrices \( Q_i \in \mathbb{R}^{n_x \times n_x}, M_i \in \mathbb{R}^{n_x \times n_x}, X \in \mathbb{R}^{n_y \times n_x}, Z_i \in \mathbb{R}^{n_u \times n_u} \) for \( i \in \Omega_N, \) and positive scalars \( \epsilon, \gamma \) satisfying the following optimization:

\[
\text{minimize } \gamma^2
\]

subject to (29), (30), (31) and the following conditions:

\[
\begin{bmatrix}
Q_i \\
(M_i C_{\Omega}) \ast \\
C_{\Omega} Q_i - X C_{\Omega} - \epsilon M_i^T \\
C_{\Omega} Q_i
\end{bmatrix}
\geq
\begin{bmatrix}
0 \\
\ast \\
\ast \\
1
\end{bmatrix}
\]

where \( i \in \Omega_N, \) \( l \in \Omega_m, \) \( m \in \Omega_q. \) Then, the SOF controller (21) with the control gains given in (33) solves Problem 1. Moreover, the system constraints \( |u(t)| \leq \bar{u} \) and \( x(t) \in D_x \) are enforced for \( \forall t \geq 0. \)

**Proof.** Multiplying (39) by \( \eta(\omega) \geq 0 \) and summing up for all \( i \in \Omega_N, \) we obtain

\[
\sum_{i=1}^{N} \eta_i(\omega) Q_i \geq \phi^2 I
\]

which implies that

\[
x(0)^T Q^{-1} x(0) \leq \phi^2 x(0)^T x(0) \leq 1
\]

for \( \forall x(0) \in D^{\text{R}_{n_x}} \) such that \( x(0) \leq \phi. \) This means that condition (39) guarantees \( V(x(0)) \leq 1. \) Now, multiplying by \( \eta_i(\omega) \geq 0 \) and summing up for all \( i \in \Omega_N \) yields

\[
\begin{bmatrix}
Q(\omega) \\
(M_i C_{\Omega}) \ast \\
C_{\Omega} Q_i - X C_{\Omega} - \epsilon M_i^T \\
C_{\Omega} Q_i
\end{bmatrix}
\geq
\begin{bmatrix}
0 \\
\ast \\
\ast \\
1
\end{bmatrix}
\]

Pre- and postmultiplying (43) with \( \begin{bmatrix} I & 0 & 0 & 0 \end{bmatrix} \) \( \times \) \[ 0 \quad I \quad M(\omega) X^{-1} \]
and its transpose, we obtain (44) after some simple manipulations.

\[
\begin{bmatrix}
Q(\omega) \\
(K_i C_{\Omega} Q(\omega) )\ast \\
(K_i C_{\Omega} Q(\omega)) \ast \ast
\end{bmatrix}
\geq
\begin{bmatrix}
0 \\
\ast \\
\ast \\
\ast
\end{bmatrix}
\]

for \( \forall x \in D^{R_{n_x}}. \) Since (see also (42))

\[
x(t)^T Q(\omega)^{-1} x(t) \leq x(0)^T Q(\omega)^{-1} x(0) \leq 1, \ \forall t \geq 0
\]

it follows from (45) that

\[
x(t)^T (K_i C_{\Omega} Q(\omega))\ast \leq \bar{u}^2, \ \ m \in \Omega_m
\]

which means that \|u(t)\| \leq \bar{u}, \forall t \geq 0.

Applying Schur complement lemma to (41), then multiplying the result by \( \eta_i(\omega) \geq 0 \) and summing up for all \( i \in \Omega_N, \) we obtain

\[
Q(\omega)^{-1} \geq H^{(m)} (\Omega_m), \forall m \in \Omega_q.
\]

Combining with (46), this latter condition implies clearly that

\[
1 \geq x^T Q^{-1} x \geq x^T H^{(m)} (\Omega_m) x, \ \forall m \in \Omega_q,
\]

which guarantees that \( x \in D_x, \) see [18, Chapter 5]. The rest of the proof follows directly from the result of Theorem 1.

**Remark 7.** By a judicious introduction of the scalar \( \epsilon \) and the slack variable \( X \) into the design conditions in Theorems 1 and 2, the complex couplings between Lyapunov matrices, control feedback gains and state-space matrices can be avoided. This enables an LMI-based formulation with a line search over a scalar for SOF control without explicitly requiring any matrix equality constraint and/or matrix rank condition as in most of existing works, see [19] for a recent survey. The proposed SOF control design belongs to the class of \( S \)-variable approach discussed in [32]. Some other notable SOF control results for linear systems based on \( S \)-variable approach can be found in [31], [33], [34] and related references.

**Remark 8.** The design conditions in Theorems 1 and 2 are a set of LMIs with a line search over \( \epsilon. \) The control gains \( K_i, i \in \Omega_N, \) can be easily computed with YALMIP toolbox and SDPT3 solver [35] performing a line search for \( \epsilon \) over a logarithmic scale in \([10^{-6}, 10^6]).\]

**Remark 9.** For multiobjective control design, the proposed control approach offers a possibility to use \( V(x) \) defined in (23) to guarantee the \( \mathbb{H}_2 \) control performance as in Theorem 1 and a new Lyapunov function \( V(x) = x^T \left( \sum_{i=1}^{N} \eta_i(\omega) Q_i \right)^{-1} x, \) where \( Q_i \geq 0, \) for \( \forall i \in \Omega_N, \) to enforce the constraints \( |u(t)| \leq \bar{u} \) and \( x(t) \in D_x \) for \( \forall t \geq 0. \) Although it could help to reduce further the design conservatism, this may lead, however, to additional computational burden to compute the SOF controller (21) with the line search described above. As shown in the next section, Theorem 2 can provide an effective SOF controller for direct tilt control of the SMERA vehicle with a reasonable numerical complexity.
V. SIMULATION RESULTS AND DISCUSSIONS

The nonlinear model (1) of the SMERA vehicle is used to simulate the performance of the SOF controller (21) designed in Section IV. It is important to note that a validation study of model (1) with experimental data collected from the SMERA vehicle was carried out to identify the vehicle parameters. Moreover, due to industrial confidentiality reasons, all the result figures are slightly scaled so that the vehicle characteristics are not revealed. The following state constraints are considered for the control design:

\[
|\theta(t)| \leq 0.35 \text{ [rad]}, \quad |a_{\text{per}}(t)| \leq 1 \text{ [m/s}^2] 
\]  (47)

Note that the first state constraint aims to prevent the vehicle rollover while cornering, and the second one is directly related to the comfort of passengers. It follows from (7) that

\[
a_{\text{per}}(v_x) = G(v_x)x_p + G_2B_3\delta,
\]

where \(G(v_x) = G_1(v_x) + G_2A_p(v_x)\). Using the variable change of scheduling parameter as described in Section III-D together with the sector nonlinearity approach [27] yields

\[
a_{\text{per}}(\omega) = \sum_{i=1}^{2} \eta_i(\omega)G_i x_p + G_2B_3\delta,
\]

where \(G_1 = G(\omega_{\text{min}})\) and \(G_2 = G(\omega_{\text{max}})\). Now, the state constraints (47) can be easily put in the form (38) for control design. The control input constraint \(\bar{u} = 40 \text{ [N}m]\) is the physical limitation of the DTC actuator\(^2\). Solving the optimization problem in Theorem 2 leads to the following result:

\[
K_1 = [3059.4 - 46142 = 5772.7 937.16 31480 5693.5] \quad K_2 = [3447.1 - 38962 = 3848.6 827.72 35565 3864.9] \quad (48)
\]

and \(\gamma = 27.3\), with \(\epsilon = 0.012\). The computation time to perform the line search described in Remark 8 is about 197 seconds. Observe that the two control gains corresponding to LPV model (15) are significantly different. This also justifies a posteriori the interest of using LPV controller (21) to improve the closed-loop performance since the vehicle speed is time-varying. Solving the same design conditions while imposing \(Q_1 = Q_2 = Q\) (i.e., quadratic approach), we obtain \(\gamma_{\text{quad}} = 34.4 > \gamma\), with \(\epsilon_{\text{quad}} = 0.003\) and a line search computation time of about 124 seconds. Thus, the quadratic approach leads to more than 20% of degradation in terms of \(H_2\) performance for this application. This confirms the interest of considering the physical limitations of both vehicle speed and acceleration into the control design to reduce the conservatism, see Remark 6.

A. Scenario 1: Vehicle Circular Trajectory

This scenario represents a situation for which the SMERA vehicle takes a medium-sized roundabout with a constant speed \(v_x = 6\) [m/s]. As depicted in Fig. 5 (a), the vehicle starts turning at \(t = 2s\) and the steering angle \(\delta\) gradually attains its absolute maximal value 0.22 [rad] at \(t = 8s\). Then, the vehicle performs a circular trajectory with a constant radius \((R \approx 19 \text{ [m]}\), see Fig. 5 (b). Note that this test scenario is much challenging compared to those tested in [8], [11] with a constant radius about 500 [m]. Observe in Fig. 5 (c) that the perceived acceleration \(a_{\text{per}}(t)\) is quite small in the transient phase. In particular, this acceleration is also perfectly regulated during the circular trajectory. Fig. 5 (d) shows that the tilt torque \(M_t\) is within the physical limitations of DTC actuator during the whole test scenario. Fig. 6 depicts the closed-loop behavior of the vehicle obtained with LPV controller given by Theorem 1. It is stressed that without any guarantee on the control input amplitude, the value of the designed input \(u(t)\) becomes excessively large during roundabout taking, which causes a saturation of DTC actuator as depicted in Figs. 6 (a) and (b), respectively. As a result, the perceived acceleration cannot be regulated in this case, see Fig. 6 (c). Moreover, the vehicle variables tend to be saturated with excessive amplitudes when the vehicle takes the roundabout as shown in Figs. 6 (c), (d), (e) and (f). It is important to note also that a similar closed-loop behavior of the SMERA vehicle is obtained when using the gain-scheduling controller proposed in [6]. This clearly demonstrates the interest of considering the DTC actuator limitations in the \(H_2\) control design. Furthermore, the gain scheduling technique used in [6] can lead to a tedious and time-consuming design procedure without any rigorous guarantee of the closed-loop performance. These facts emphasize the contributions of the proposed control method compared to the existing literature.

\[\text{Fig. 5. Scenario 1: Closed-loop behavior of SMERA when actuator limitations are taken into account in the } H_2 \text{ control. (a) steering angle; (b) vehicle trajectory; (c) perceived acceleration; (d) tilt torque.}\]

\[\text{Fig. 6. Scenario 1: Closed-loop behavior of SMERA when actuator limitations are not taken into account in the } H_2 \text{ control. (a) control input; (b) tilt torque; (c) perceived acceleration; (d) yaw rate; (e) tilt angle; (f) tilt rate.}\]

B. Scenario 2: Bend-taking with Time-Varying Speed

This scenario represents a situation for which the SMERA vehicle takes two successive bends with a highly time-varying vehicle speed, see Figs. 7 (a) and (b). To demonstrate the interest of taking into account the time-varying nature of the vehicle speed in the DTC control design, the performance comparison between two following SOF controllers is considered:

- **LPV controller** whose feedback gains are given in (48).
- **Linear time-invariant (LTI) controller** whose linear feedback gain is synthesized under similar design conditions as for the above LPV controller with a constant speed \(v_x = 8\) [m/s].

The comparison results are depicted in Figs. 7 (c), (d), (e), (f), (g) and (h). It can be observed that the LPV controller provides a clear

\[\text{For real-time implementation, the hard constraint on the physical limitation of the tilt torque is guaranteed by the "Saturation" block in Simulink.}\]
performance improvement compared to the LTI one, especially in terms of acceleration regulation and transient behavior of the tilt torque $M_t$. Fig. 7 (c) also shows that the perceived acceleration is well regulated by the LPV controller with an acceptable maximal amplitude about 0.7 [m/s²] during transient phases. The tilt torque $M_t$ remains within its saturation limits for both SOF controllers during the whole test as shown in Fig. 7 (d). Note that the considered test scenario is much more challenging than those used in other DTC control contexts of NTVs [6], [8], [11], [21], i.e., driving scenarios with low and/or constant vehicle speed and very large bends. It is important to note also that for this challenging scenario, the gain-scheduling controller proposed in [6] also provides an unstable closed-loop behavior, which is not shown here for brevity.

![Fig. 7. Scenario 2: Control performance comparison. (a) steering angle; (b) vehicle speed; (c) perceived acceleration; (d) tilt torque; (e) lateral speed; (f) yaw rate; (g) tilt angle; (h) tilt rate.](image)

VI. CONCLUDING REMARKS

This paper proposes a new LPV control method for automatic DTC of NTVs. For real-time control implementation, only common sensors available on commercial vehicles are required and the robust SOF controller is of the simplest structure. The proposed DTC method is formulated as an LMI-based optimization in multiobjective setting. Based on the use of a PDLF, the information on both speed and acceleration limitations is incorporated into the design of robust DTC controllers to reduce the conservatism. The effectiveness of the proposed method is clearly demonstrated with realistic driving scenarios. Our future works focus on the shared control between a human driver and a STC system (see for instance [24]) in the presence of DTC control actions. Moreover, experimental validations of the proposed DTC method in real-world driving conditions should be also investigated.

REFERENCES