Robust Control of Networked Systems with Variable Communication Capabilities and Application to a Semi-Active Suspension System

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Abstract—This paper is concerned with a robust control problem of a class of networked systems operated within a multiple communication channels (MCCs) environment. A practical scenario is considered that the active channel in such MCCs for the data communication is switched and the switching is governed by a Markov chain. For each channel, two network-induced imperfections, time delays and packet dropouts with different characteristics are taken into account. Suppose that the practical plant is subject to energy-bounded disturbance and norm-bounded uncertainties, a robust controller is designed to ensure that the closed-loop system is robustly stable and achieves a disturbance attenuation index against the phenomenon of channel switching. A semi-active suspension system is introduced to illustrate the effectiveness, applicability of the proposed approach and to demonstrate the advantages of the MCCs scheme within the channel-switching framework.

Index Terms—Channel switching, controller design, multiple communication channels (MCCs), network control systems (NCSs), semi-active suspension system

I. INTRODUCTION

During the past several decades, great importance has been attached to network-based control problems. Control systems constructed via communication networks have emerged in a wide range of application fields, such as intelligent vehicles [1], [2], robot localization [3], traffic system management [4], power systems [5], cloud-aided suspension systems [6], large-scale chemical processes [7], etc. The inherent advantages of network control systems (NCSs), as discussed in [8], include low cost, flexible structures, simple implementation and user-friendly maintenance requirements. So far, the above benefits have substantially motivated research interests in the development of advanced control algorithms of NCSs. Consequently, several standard control methodologies such as sliding model control, adaptive control, fuzzy logic control and model predictive control have been extended to the scenarios where networked schemes are employed [9]–[23].

Despite the aforementioned benefits of NCSs, it is worth mentioning that NCSs usually suffer from network-induced imperfections which may dramatically reduce the data transmission reliability. To be specific, network-induced issues such as data-transmission delays and intermittent packet dropouts are frequently encountered in engineering systems, and in return pose great challenges to the design and operation of NCSs [24], since they may deteriorate system performance or even lead to instability of an entire system. Up to date, several approaches have been proposed to deal with these networked problems. To name a few, stability analysis was carried out for a class of NCSs by exploiting a switched system model [25], a stability region approach was developed for stability analysis of NCSs [26], an event-triggered communication and control co-design problem has been addressed [27], a fault detection problem for NCSs was investigated in [28].

Although inferior data transmission reliability may explicitly degrade the performance of NCSs, almost all existing works for NCSs were carried out by employing one single communication channel for information exchange, which is unfavorable from a practical point of view. In practice, multiple communication channels (MCCs) can potentially improve the communication performance, flexibility as well as reliability by providing multiple availabilities to alleviate transmission interferences [29]. MCCs schemes were considered for the studies of NCSs in [30], [31]. In the context of MCCs, a practical consideration is to use only one channel for data transmission at one time. In addition, the active channel for data transmission would be switched and the switching is subject to certain prescribed rules. This is mainly because that each channel is featured by fluctuating performance affected by environmental changes, system failures, object movement and communication burdens. As the channel switching is a stochastic sequence, one natural way is to assume this random switching sequence is governed by a Markov chain that has been extensively utilized to depict various random processes, which, together with some preliminaries and theoretical analysis of this paper, have been discussed in [32]. Although some results were reported for MCCs for more reliable data.
transmission, we notice that little attention has been given to control system designs of networked systems with MCCs, especially the scenarios where channel switching is explicitly considered, which will substantially benefit modern NCs with complex structures, large scales and vulnerable communication environments.

Motivated by above observations, we investigate a robust control problem for a class of NCs with MCCs in this work. We consider a practical scenario where the controllers are embedded in a remote agent that receives measurements from sensors and sends control signals to actuators over the MCCs. The treatment in terms of the controller design problem is different from existing studies where only one communication channel is involved. Every communication channel has time-varying performance affected by internal and external influences. We consider that the channel for communication is switched and the switching is governed by a continuous-time Markov process. Bernoulli random distribution is employed to characterize the data-missing phenomena occurring in both sensor-to-controller and controller-to-actuator communication channels. A class of Lyapunov-Krasovskii functionals (LKFs) is constructed to design the controllers that account for network-induced time-varying delays, channel communication packet dropouts and system parameter uncertainties. With the proposed approach, effective controllers for a semi-active suspension system manipulated via a remote agent are developed such that desirable control performance is guaranteed.

The rest of this paper is organized as follows. In Section II, the robust controller design problem is formulated for a class of uncertain NCs with MCCs and several indispensable theories are reviewed. Section III is devoted to the stability and performance analysis with an LKF-based approach. Explicit conditions for the existence of potential controllers are presented, and the controller design procedure is formulated. In Section IV, a semi-active suspension system model operated within a cloud-aided framework is utilized for effectiveness and applicability verification of the proposed method. Finally, the conclusions are drawn in Section V.

Notation: We use standard notations throughout this work. The superscript “\(^T\)” stands for matrix transposition. \(L_2[0, \infty)\) represents the space of square-integrable functions on \([0, \infty)\), and for \(w(t) \in L_2[0, \infty), \|w\|^2_2 = \int_0^\infty w(t)^T w(t) dt\). In symmetric block matrices or long matrix expressions, \(\ast\) is introduced as an ellipsis for the terms that are induced by symmetric and† introduced as an ellipsis for the terms that are induced by \(\ast\). \(\text{Sym}(A)\) is a shorthand notation for \(A + A^T\). The Kronecker product is denoted by \(\otimes\). The notation \(P > 0\) (\(P \geq 0\)) implies that \(P\) is symmetric and positive (semi-positive) definite.

II. PROBLEM FORMULATION AND PRELIMINARIES

In this work, a class of network-based systems subject to system uncertainties that is described by the following continuous-time dynamics is taken into account:

\[
\dot{x}(t) = (A + \Delta A(t))x(t) + (B + \Delta B(t))u(t) + B_w w(t),
\]

\[
y_0(t) = Cx(t) + Du(t),
\]

\[
z(t) = L_0x(t) + L_1u(t),
\]

(1)

where \(x(t) \in \mathbb{R}^n\) is the state vector; \(u(t) \in \mathbb{R}^p\) denotes the control input vector; \(y_0(t) \in \mathbb{R}^r\) represents the measured output vector; \(z(t) \in \mathbb{R}^m\) denotes the controlled output; \(w(t) \in \mathbb{R}^q\) is the external disturbance belonging to \(L_2[0, \infty)\). \(A, B, B_w, C, D, L_0\) and \(L_1\) are known constant system matrices with compatible dimensions. The uncertain parameters \(\Delta A(t)\) and \(\Delta B(t)\) are time-varying matrices satisfying the following assumptions: \(\Delta A(t) = H_1F_1(t)E_1\), \(\Delta B(t) = H_2F_2(t)E_2\), respectively, where \(H_i \in \mathbb{R}^{m \times s}, E_i \in \mathbb{R}^{s \times n}, i = \{1, 2\}\), are known constant matrices with compatible dimensions, and \(F_i(t) \in \mathbb{R}^{s \times s}, i = \{1, 2\}\) are unknown time-varying matrix functions satisfying \(F_i(t)F_i(t)^T \leq I_s\), \(\forall t \geq 0\).

An MCCs framework consisting of \(N\) independent communication channels for data transmission is taken into account. The measured output vector of the system \(y_0\) is sent to the corresponding controllers via one of the available channels. We note that at one time, only one of the available \(N\) channels is used for data transmission. The channel selection is realized by taking advantage of a channel scheduler that can be used to perform channel switching based on a prescribed criterion.

**Remark 1:** The selection of an appropriate scheduler depends on the factors we are most concerned with. Typically, a channel scheduler can use the minimum time delay, minimum packet dropout rate, economic communication cost in terms of communication as the channel switching rules. Other channel selection criteria are referred to [33], [34].

We denote \(c_i\) as the channel switching signal that takes values in a finite set \(C = \{1, 2, \ldots, N\}\) which indicates the number of the channel that is currently being adopted. Since the channel switching sequence is stochastic, we assume the overall channel switching is governed by a continuous-time Markov process \(\{c_t \in C, t \geq 0\}\) with the infinitesimal generator, \(\Lambda := [\lambda_{ij}], i, j \in C\), where \(\lambda_{ij} \geq 0, \forall j \neq i, \lambda_{ii} = -\sum_{j \neq i} \lambda_{ij}\) [35]. Then the channel transition probability of channel \(i\) to channel \(j\) can be approximated as

\[
\Pr(c_{t+\Delta} = j | c_t = i) = \begin{cases} 
\lambda_{ij} \Delta + o(\Delta), & j \neq i, \\
1 + \lambda_{ii} \Delta + o(\Delta), & j = i,
\end{cases}
\]

(2)

where \(o(\Delta)\) satisfies \(\lim_{\Delta \to 0} o(\Delta)/\Delta = 0\).

In networked systems, time delays are frequently encountered in the data transmission phases, i.e., the sensor-to-controller (s2c) phase and the controller-to-actuator (c2a) phase. The channels may be with vastly different performances in terms of this communication imperfection. Before proceeding further, we present the following assumptions on the time delays of the communication channels.

**Assumption 1:** if channel \(i, i \in C\) is selected for data transmission, the sensor-to-controller delay and controller-to-actuator delay that are, respectively, denoted as \(\tau_i^{s2c}(t)\) and \(\tau_i^{c2a}(t)\), are time-varying and satisfy \(\delta_i \leq \tau_i^{s2c}(t) \leq \tau_i\), \(\tau_i \leq \tau_i^{c2a}(t) \leq \tau_i\), with \(\delta_i\) and \(\tau_i\) being positive constant scalars that represent the lower and upper bounds of the communication delays of channel \(i\), respectively.

**Assumption 2:** It is further assumed that \(\tau_i^{s2c}(t) \leq d < \infty\), \(\tau_i^{c2a}(t) \leq d < \infty\), \(\forall i \in C\), where \(d\) is a known bound. For notational simplicity, we use \(\tau_i^{s2c}\) and \(\tau_i^{c2a}\) to represent \(\tau_i^{s2c}(t)\) and \(\tau_i^{c2a}(t)\), respectively.
Let $y_i(t)$ denote the received measurement at the controller node at time $t$, assume channel $i$ to be the communication channel, and take into account the packet dropouts existing in the sensor-to-controller communication channels, we have:

$$y_i(t) = \Theta_i^{2c} y_0(t - \tau_i^{2c}(t))$$

$$\approx \Theta_i^{2c} C x(t - \tau_i^{2c}(t)) + \Theta_i^{2c} D w(t).$$

(3)

where $\Theta_i^{2c} := \text{diag} \{ \theta_i^{2c}, \theta_i^{2c}, \ldots, \theta_i^{2c} \}$ is a matrix of mutually independent random variables $\theta_i^{2c}$, $i \in \mathcal{C}$ and $j = 1, 2, \ldots, r$, denoting the packet arrival rate of sensor $i$ via channel $i$. Without loss of generality, we assume $\theta_i^{2c}$ to be distributed over interval $[0, 1]$ with mean $\mu_i^{2c}$ and standard deviation $\epsilon_i^{2c}$. In the sequel, we denote $\Theta_i^{2c} = \mathbb{E}[\Theta_i^{2c}] = \text{diag} \{ \mu_i^{2c}, \mu_i^{2c}, \ldots, \mu_i^{2c} \}$.

Remark 2: It is sensible to retain time delays in the system state term while ignoring the delays for the disturbance term. The reasons are twofold: 1) If system disturbance $w(t)$ can be described by a typical function, the value will not fluctuate too much and will be similar to the one at time $t - \tau_i^{2c}(t)$ if the time delay for each channel is constrained within a small interval, which is common in practice; 2) If the disturbance is a white noise sequence, then $w(t)$ is considered to be equal to $w(t - \tau_i^{2c}(t))$. Consequently, (3) is a well-balanced model.

We deploy $N$ controllers for the $N$ communication channels. For channel $i$, the associated controller designed as:

$$\dot{x}_c(t) = A(c_i) x_c(t) + B(c_i) y_0(t),$$

$$u_0(t) = C(c_i) x_c(t),$$

(4)

where $A(c_i), B(c_i)$ and $C(c_i)$ are controller parameters to be designed $\forall i \in \mathcal{C}$, and $x_c \in \mathbb{R}^n$. We note that each controller is designed for one communication channel, and the Ncontrollers are embedded in the remote agent such that the implementational complexity will not increase significantly.

Then, taking into account the time delays and packet dropout phenomena existing in the controller-to-actuator communication channels, we have

$$u(t) = \Theta_i^{2a} u_0(t - \tau_i^{2a}(t))$$

$$\approx \Theta_i^{2a} K_C(c_i) x_c(t - \tau_i^{2a}(t)).$$

(5)

where $\Theta_i^{2a} := \text{diag} \{ \theta_i^{2a}, \theta_i^{2a}, \ldots, \theta_i^{2a} \}$ is a matrix of mutually independent random variables $\theta_i^{2a}$, $i \in \mathcal{C}$ and $j = 1, 2, \ldots, p$, denoting the packet arrival rate of control signal $j$ via channel $i$ from the remote agent to the actuator. Similarly, we assume this packet arrival rate also follows a normal distribution and we denote $\Theta_i^{2a} = \mathbb{E}[\Theta_i^{2a}] = \text{diag} \{ \mu_i^{2a}, \mu_i^{2a}, \ldots, \mu_i^{2a} \}$.

Remark 3: It is assumed that there are certain overlaps in terms of time delays and packet arrival rates in both sensor-to-controller channels and controller-to-actuator channels over the MCCs, i.e., $\bigcap_{i \in \mathcal{C}} [I, \bar{\tau}_i] \neq \emptyset$, $\Pr (\Theta_i < \Theta_j) \neq 0$, $\forall i, j \in \mathcal{C}$, which implies that there is no universally best or worst channel that could be constantly adopted or abandoned.

By defining $\eta(t) = [x^T(t) \quad x_c^T(t)]^T$ and combining (1), (3), (4) and (5), we have the following augmented system:

$$\dot{\eta}(t) = \bar{A}(c_i)\eta(t) + \bar{A}_1(c_i)x(t - \tau_i^{2c}(t))$$

$$+ \bar{A}_2(c_i)x_c(t - \tau_i^{2a}(t)) + \bar{B}_w(c_i)u(t),$$

$$z(t) = L_0 \eta(t) + L_1 x_c(t - \tau_i^{2c}(t)),$$

$$\eta(s) = \phi(s), \quad s \in [\bar{\tau}, 0],$$

(6)

where

$$\bar{A}(c_i) := [A + \Delta A \quad 0_{n \times n}] {A}_1(c_i) := [0_{n \times n} \quad K_B(c_i) \Theta_i^{2c} C],$$

$$\bar{A}_2(c_i) := [(B + \Delta B)\Theta_i^{2a} K_C(c_i)], \quad \bar{L}_0 := [L_0 \quad 0_{m \times n}],$$

$$\bar{B}_w(c_i) := [B_w \quad K_B(c_i) \Theta_i^{2c} D], \quad \bar{L}_1 := L_1 \Theta_i^{2a} K_C(c_i),$$

$$\bar{\tau} := \max_{i \in \mathcal{C}} \bar{\tau}_i,$$

and $\phi(\cdot) \in L_2[\bar{\tau}, 0]$ is the initial condition.

Definition 1: [35] System (6) with $w(t) \equiv 0$ is said to be stochastically stable (SS) if there exists a constant $T(c_0, \phi(\cdot)) > 0$, such that $\mathbb{E}[\|z(t)\|^2]\preceq T(c_0, \phi(\cdot))$ where $\phi(\cdot) \in L_2[\bar{\tau}, 0]$ is the initial condition of system (6) with $\bar{\tau} = \max_{i \in \mathcal{C}} \bar{\tau}_i$.

The $H_\infty$ control problem addressed in this paper can be formulated as follows: given system (1) and a prescribed level of noise attenuation $\gamma > 0$, determine linear controllers in the form (4) such that the controlled system is stochastically stable and, assuming zero initial conditions, we have

$$\mathbb{E}[\|z(t)\|^2] \leq \gamma^2 \|w\|^2.$$

(7)

Before presenting the main results, the following lemmas that will be used in the subsequent analysis are introduced.

Lemma 1: [36] Let $L = LT^T$, $H$ and $E$ be real matrices. If $F$ satisfies $FF^T \preceq I$, then $L + HFE + ET^THT^T < 0$, if and only if there exists a positive scalar $\varepsilon > 0$ such that $\varepsilon I - ET^T > 0$, or equivalently

$$\begin{bmatrix} L & H \\ H^T & \varepsilon I \end{bmatrix} < 0.$$

(8)

Lemma 2: (Chebyshev-like inequality) [37] If $f, g: [a \quad b] \rightarrow \mathbb{R}^n$ are similarly ordered, that is,

$$\begin{bmatrix} f(x) \quad g(y) \end{bmatrix} \begin{bmatrix} f(x) \quad g(y) \end{bmatrix} \geq 0, \quad \forall x, y \in [a \quad b],$$

then the following inequality holds:

$$\frac{1}{b - a} \int_a^b f(x)g(x)dx \geq \frac{1}{b - a} \int_a^b f(x)dx \int_a^b g(x)dx.$$

(9)

Lemma 3: (Projection Lemma) [36] Let $W = W^T \in \mathbb{R}^{m \times n}$, $U \in \mathbb{R}^{m \times k}$, and $V \in \mathbb{R}^{k \times n}$ be given matrices, and suppose that $\text{rank}(U) < n$ and $\text{rank}(V) < n$. The following LMI problem:

$$W + U^TA^TV + V^TUXU < 0.$$

(10)
is solvable for $X$ if and only if
\[
U_s^TWU_s < 0 \text{ if } U_s = 0, \quad U_s \neq 0, \\
V_s^TWV_s < 0 \text{ if } U_s = 0, \quad V_s \neq 0, \\
U_s^TWU_s < 0, \quad V_s^TWV_s < 0, \quad \text{if } U_s \neq 0, \quad V_s \neq 0,
\]
with $U_s$ and $V_s$ being the right null spaces of $U$ and $V$, respectively.

### III. MAIN RESULTS

In this section, we carry out the stability analysis and present the controller design procedure. First, we derive sufficient conditions to ensure the stochastic stability and the $H_{\infty}$ performance bound in the following theorem.

**Theorem 1:** We denote $K_A(i)$, $K_B(i)$, $K_C(i)$, $i \in \mathcal{C}$ as given controller parameters and use symbol $\gamma$ to represent a prescribed positive scalar. Then the closed-loop system in (6), with $w(t) = 0$, is said to be stochastically stable and $\mathbb{E}[\|z(t)\|^2_2] \leq \gamma^2 \|w(t)\|^2_2$ if there exist positive definite matrices $P(1)$, $P(2)$, $\cdots$ $P(N) \in \mathbb{R}^{n \times 2n}$, $Q_1, \cdots, Q_4 \in \mathbb{R}^{n \times n}$, $R_1, R_2 \in \mathbb{R}^{n \times n}$, positive constant $\epsilon$, and matrix $\tilde{G} \in \mathbb{R}^{(8n + q) \times 2n}$ such that
\[
\begin{bmatrix}
\Sigma_1(i) & \Sigma_2(i) \\
\Sigma_3 & \Sigma_4
\end{bmatrix} < 0
\]
for all $i \in \mathcal{C}$, where
\[
\Sigma_1(i) := \begin{bmatrix} T_s^T R \mathcal{A}_1 & P(i) M_1 \\ M^T Q(i) M & 0 \end{bmatrix}, \\
\Sigma_2(i) := \begin{bmatrix} \tilde{G} \tilde{H} e^{\mathcal{E}T} \begin{bmatrix} 0_{2n \times n} \\ 0_{n \times n} \end{bmatrix} \\ \bar{G}_1 \tilde{H} e^{\mathcal{E}T} \begin{bmatrix} 0_{2n \times n} \\ 0_{n \times n} \end{bmatrix} \end{bmatrix}, \\
\Sigma_3 := \text{diag}\{-\epsilon I_{2n}, -\epsilon I_{2n}, -I_m\}, \\
\Sigma_4 := \begin{bmatrix} A & 0_{n \times n} & 0_{n \times n} \\ 0_{n \times n} & A & 0_{n \times n} \\ 0_{n \times n} & 0_{n \times n} & B \Theta_{\mathcal{E}}^2 K_C(i) \\ 0_{n \times n} & 0_{n \times n} & B \Theta_{\mathcal{E}}^2 K_B(i) \end{bmatrix}, \\
\mathcal{A}_0(i) := \begin{bmatrix} I & 0_{n \times n} & 0_{n \times n} \\ 0_{n \times n} & I & 0_{n \times n} \\ 0_{n \times n} & 0_{n \times n} & K_A(i) \Theta_{\mathcal{E}}^2 D \end{bmatrix}, \\
\mathcal{M} := \begin{bmatrix} M_1 & M_2 \\ M_3 & M_4 \\ M_5 & M_6 \\ M_7 & M_8 \\ T_s^T & T_s^T \end{bmatrix}, \\
\mathcal{I}_1 := [I_n, \ 0_{n \times n}], \\
\mathcal{I}_2 := [0_{n \times n}, \ I_n], \\
\mathcal{I}_3 := [0_{n \times n}, \ 0_{n \times n}], \\
\mathcal{I}_4 := [0_{n \times n}, \ 0_{n \times n}], \\
\mathcal{I}_5 := [0_{n \times n}, \ 0_{n \times n}], \\
\mathcal{I}_6 := [0_{n \times n}, \ 0_{n \times n}], \\
\mathcal{I}_7 := [0_{n \times n}, \ 0_{n \times n}], \\
\mathcal{I}_8 := [0_{n \times n}, \ 0_{n \times n}], \\
\mathcal{L}(i) := \begin{bmatrix} I_n & 0_{n \times n} \\ 0_{n \times n} & I_n \end{bmatrix}, \\
\mathcal{R}(i) := \begin{bmatrix} \mathcal{I}_1 \ 0_{n \times n} \end{bmatrix}, \\
\mathcal{Q}(i) := \text{diag}\{\Xi(i), - (1 - d) \Delta_1, - (1 - d) \Delta_2, - Q_3, - Q_4, - \tau^2 I_q, - R_1, - R_2\}, \\
\mathcal{E} := \text{max} \{\hat{\tau}, \ 0\}, \\
g := 1 + \lambda(\mathcal{E}), \\
\Xi(i) := \sum_{j=1}^{N} \lambda_{ij} P(j), \\
\mathcal{F} := \text{diag}\{F_1, F_2\}, \\
\tilde{F}(i) := \begin{bmatrix} 0_{n \times 2n} & E_1 & 0_{n \times 2n} & 0_{n \times n} & 0_{n \times n} & 0_{n \times (2n+q)} \\ 0_{n \times 2n} & 0_{n \times 2n} & 0_{n \times n} & E_2 \Theta_{\mathcal{E}}^2 K_C(i) & 0_{n \times (2n+q)} \\ 0_{n \times 2n} & 0_{n \times 2n} & 0_{n \times n} & 0_{n \times (2n+q)} & 0_{n \times (2n+q)} \end{bmatrix}.
\]

**Proof:** A Markovian Lyapunov–Krasovskii functional (LKF) $V(\eta(t), c_1, t)$ is constructed as follows
\[
V(\eta(t), c_1, t) := \sum_{i=1}^{4} V_i(\eta(t), c_1, t),
\]
where
\[
V_1(\eta(t), c_1, t) := \eta^T(t) P(c_1) \eta(t), \\
V_2(\eta(t), c_1, t) := \int_{t-	au c_1(t)}^{t} x^T(s) Q_1 x(s) ds + \int_{t-	au^2 c_1(t)} x^T(s) Q_2 x(s) ds \\
+ \int_{t-	au}^{t} x^T(s) Q_3 x(s) ds + \int_{t-	au}^{t} x^T(s) Q_4 x(s) ds \\
:= V_{21} + V_{22} + V_{23} + V_{24}, \\
V_3(\eta(t), c_1, t) := \int_{t-	au}^{t} \int_{t+	heta}^{t+	heta} \bar{x}^T(s) Q_1 \bar{x}(s) ds d\theta, \\
V_4(\eta(t), c_1, t) := \int_{t-	au}^{t} \int_{t+	heta}^{t+	heta} \bar{x}^T(s) Q_2 \bar{x}(s) ds d\theta, \\
\text{with } \bar{x} \text{ already stated in Theorem 1.}
\]

We denote $\mathcal{D}$ as a weak infinitesimal generator of a random process $\{\eta(t), c_1\}$ and define
\[
\mathcal{L} V(\eta(t), c_1) := \lim_{\Delta \to 0} \frac{1}{\Delta} \left[ \mathbb{E}[V(\eta(t + \Delta), c_{1+\Delta})] - V(\eta(t), c_1) \right].
\]

If $DF(\eta(t), c_1, t) + z^T(t) z(t) - \gamma^2 u^T(t) u(t) < 0$, then the closed-loop system in (6) is stochastically stable and the $H_{\infty}$ performance bound in (7) is satisfied. Applying the weak infinitesimal generator to the LKF, we have
\[
\mathcal{D} V_1(\eta(t), c_1, t) := 2 \eta^T(t) P(c_1) \eta(t) + \eta^T(t) \sum_{j=1}^{N} \lambda_{c_1 j} P(j) \eta(t).
\]

By applying the infinitesimal generator to $V_2(x(t), c_1, t)$ and combining the transition probabilities defined in (2), we have
\[
\mathcal{D} V_{21}(\eta(t), c_1, t) := \mathcal{L} V_{21}(\eta(t), c_1, t) := \lim_{\Delta \to 0} \frac{1}{\Delta} \left[ \mathbb{E}[V_{21}(\eta(t + \Delta), c_{1+\Delta}, t + \Delta)|\{\eta(t), c_1\}] - V_{21}(\eta(t), c_1, t) \right] \\
= \sum_{j \in \mathcal{E}} \int_{t-	au c_1}^{t} x^T(s) Q_1 x(s) ds \\
+ x^T(s) Q_1 x(s) - (1 - \tau^2 c_1) x^T(t) (s - \tau^2 c_1) Q_1 x(t - \tau^2 c_1),
\]
Similarly, we have that
\[ D V_2(\eta(t), c_i, t) = \sum_{j \in C} \lambda_{ij} \int_{t - \tau^{c_{ij}}}^{t} x^T(s)Q_2x(s)ds + x^T_c(t)Q_2x_c(t) - (1 - \tau^{c_{ij}})x^T_c(t - \tau^{c_{ij}})Q_2x_c(t - \tau^{c_{ij}}). \] 
Moreover, it is calculated that
\[ D V_3(\eta(t), c_i, t) + L V_4(\eta(t), c_i, t) = x^T(t)(Q_3 + Q_4)x(t) - x^T(t - \tau^{c_{ij}})Q_3x(t - \tau^{c_{ij}}) - x^T(t - \tau^{c_{ij}})Q_4x(t - \tau^{c_{ij}}). \]
From (14), (15), (16), and Assumption 1, it follows that
\[ D V_2(\eta(t), c_i, t) \leq x^T(t) \sum_{i=1,3,4} Q_i x(t) + x^T_c(t)Q_2x_c(t) \]
\[ + \sum_{j \in C} \lambda_{ij} \int_{t - \tau^{c_{ij}}}^{t} x^T(s)Q_1x(s)ds \]
\[ + \sum_{j \in C} \lambda_{ij} \int_{t - \tau^{c_{ij}}}^{t} x^T(s)Q_2x_c(s)ds \]
\[ - (1 - d)x^T(t - \tau^{c_{ij}})Q_1x(t - \tau^{c_{ij}}) \]
\[ - (1 - d)x^T_c(t - \tau^{c_{ij}})Q_2x_c(t - \tau^{c_{ij}}) \]
\[ - x^T(t - \tau^{c_{ij}})Q_3x(t - \tau^{ij}) - x^T(t - \tau^{c_{ij}})Q_4x(t - \tau^{c_{ij}}). \]
Furthermore, we have:
\[ D V_4(\eta(t), c_i, t) = \bar{\lambda}(\bar{\tau} - \bar{\tau}^{c_{ij}})x^T(t)Q_1x(t) - \bar{\lambda} \int_{t - \tau^{c_{ij}}}^{t - \tau^{c_{ij}}} x^T(s)Q_1x(s)ds \]
\[ + \bar{\lambda}(\bar{\tau} - \bar{\tau}^{c_{ij}})x^T_c(t)Q_2x_c(t) - \bar{\lambda} \int_{t - \tau^{c_{ij}}}^{t - \tau^{c_{ij}}} x^T_c(s)Q_2x_c(s)ds, \]
\[ D V(t, c_i, t) = \sum_{i=1,3,4} x^T(t)Q_i x(t) - x^T(t)Q_3x(t) + x^T_c(t)Q_4x_c(t). \]
where the last inequality follows Lemma 2. Based on (17),
\[ \sum_{j=1}^{N} \lambda_{ij} \int_{t - \tau^{c_{ij}}}^{t} x^T(s)Q_1x(s)ds \]
\[ \leq \sum_{j 
eq c_i} \lambda_{ij} \int_{t - \tau^{c_{ij}}}^{t} x^T(s)Q_1x(s)ds + \lambda_{c_i c_i} \int_{t - \tau^{c_{ij}}}^{t} x^T(s)Q_1x(s)ds \]
It is also noted that \( \sum_{j 
eq c_i} \lambda_{ij} = -\lambda_{c_i c_i} \), it follows that
\[ \sum_{j=1}^{N} \lambda_{ij} \int_{t - \tau^{c_{ij}}}^{t} x^T(s)Q_1x(s)ds \]
\[ \leq -\lambda_{c_i c_i} \int_{t - \tau^{c_{ij}}}^{t - \tau^{c_{ij}}} x^T(s)Q_1x(s)ds \]
\[ \leq \bar{\lambda} \int_{t - \tau^{c_{ij}}}^{t - \tau^{c_{ij}}} x^T(s)Q_1x(s)ds. \]
Combining (27), (29), Lemma 1, and Lemma 3, it is easy to check that (11) in Theorem 1 is equivalent to \( \Psi(i) < 0 \), which implies that \( D V(q(t), q_1(t), q_2(t), q_3(t), q_4(t)) + \gamma^2 w^T(t) w(t) < 0 \). This completes the proof of Theorem 1.

Remark 4: Based on the Projection Lemma, we introduce a slack matrix \( \tilde{\Sigma} \) such that the controller parameters and Lyapunov matrices can be decoupled. We note that the decoupling procedure simplifies the analysis and design compared to many conventional methodologies [35], [38].

Now, we are in a position to address the \( H_\infty \) control design problem for system (1), i.e., calculating controller gains \( K_A(i), K_B(i) \) and \( K_C(i) \) in forms of (4) such that the error system (6) is stochastically stable with a guaranteed \( H_\infty \) bound. The following theorem gives sufficient conditions for the existence of such a controller.

**Theorem 2**: Let \( \gamma \) be a given constant representing desired attenuation level. Consider the uncertain system (1), there exist \( H_\infty \) controllers in forms of (4) such that the closed-loop system in (6) is stochastically stable and \( H_\infty \) performance in (7) is satisfied, if there exist positive-definite matrices \( P(i) = \begin{bmatrix} P_1(i) & P_2(i) \\ * & P_3(i) \end{bmatrix} \in \mathbb{R}^{2n \times 2n} \), \( i = 1, \cdots, N \), \( Q_1, \cdots, Q_4 \in \mathbb{R}^{n \times n}, R_1, R_2, G_2 \in \mathbb{R}^{n \times n} \), positive constant \( \epsilon \), constants \( q_1, \cdots, q_4, \sigma, K_A(i), K_B(i), K_C(i) \), \( i = 1, 2, \cdots, N \), such that

\[
\begin{bmatrix} \Omega_1(i) & \Omega_2(i) \\ \Sigma_3(i) & 0 \end{bmatrix} < 0
\]  

(30)

for all \( i \in \mathcal{C} \), where

\[
\Omega_1(i) := \begin{bmatrix} I_n^T R_1 M_i^T Q(M_i) \sigma^2 \epsilon^2 C \sigma C^T \end{bmatrix} + S y m \left\{ \begin{bmatrix} -\pi \otimes G \\ 0_{q \times 2 \pi} \\ 0_{q \times (n+q)} \end{bmatrix} \right\},
\]

\[
\Omega_2(i) := \begin{bmatrix} \pi \otimes H \\ 0_{q \times 2 \pi} \end{bmatrix} \epsilon^2 E^T(i) \begin{bmatrix} 0_{2 \pi \times m} \\ \Sigma_3(i) \end{bmatrix},
\]

\[
G := \begin{bmatrix} I_n & G_2 \\ \sigma I_n & G_2 \end{bmatrix}, \quad \pi := \begin{bmatrix} q_1 & q_2 & q_3 \end{bmatrix}^T,
\]

\[
\tilde{\bar{A}}(i) := \begin{bmatrix} A & K_A(i) & K_B(i) \tilde{\Theta}_c C \\ \sigma A & K_A(i) & K_B(i) \tilde{\Theta}_c C \\ 0_{n \times n} & B_w + K_B(i) \tilde{\Theta}_c D \\ 0_{n \times n} & \sigma B_w + K_B(i) \tilde{\Theta}_c D \end{bmatrix},
\]

and \( R, M_1, \bar{H}, \tilde{E}, \tilde{\Sigma}_3 \) and \( \tilde{\bar{L}}(i) \) are defined the same as in the statement of Theorem 1. Furthermore, if (30) is feasible, then the controller parameters in (4) are given as

\[
K_A(i) = G_2^{-1} \tilde{K}_A(i), \quad K_B(i) = G_2^{-1} \tilde{K}_B(c),
\]  

(31)

for all \( i \in \mathcal{C} \).

Proof: According to Theorem 1, the closed-loop system in (6) is stochastically stable if \( \tilde{E} \leq \gamma \|w(t)\|^2 \) for all \( w(t) \in L_2[0, \infty) \), if there exist positive-definite matrices \( P(1), P(2), \cdots, P(N), Q_1, \cdots, Q_4 \in \mathbb{R}^{n \times n} \), \( R_1, R_2 \in \mathbb{R}^{n \times n} \), positive constant \( \epsilon \), and matrix \( G \) such that (11) holds.

For the controller synthesis procedure, we first specify the slack matrix \( \tilde{\Sigma} \) as

\[
\tilde{\Sigma} = \begin{bmatrix} G & \Theta_c G^T & 0_{2n \times q} \\ G_1 & G_2 & G_3 & G_4 \end{bmatrix}^T,
\]  

(32)

where \( \Theta_1, \Theta_2, \) and \( \Theta_3 \) are scalar parameters to be searched.

Then we perform a congruence transformation to \( G \) by \( \text{diag} \{I_n, G_2 G_4^{-1} \} \), which yields

\[
\begin{bmatrix} I_n & 0 \\ 0 & G_2 G_4^{-1} \end{bmatrix} \begin{bmatrix} G_1 & G_2 \\ G_3 & G_4 \end{bmatrix} \begin{bmatrix} I_n & 0 \\ 0 & G_4^{-1} G_2^T \end{bmatrix} = \begin{bmatrix} G_1 & G_2 G_4^{-1} G_2^T \\ G_2 G_4^{-1} G_2^T & G_2 G_4^{-1} \end{bmatrix}.
\]

Consequently, we are able to, without loss of generality, directly specify the matrix \( G \) as

\[
G = \begin{bmatrix} G_1 & G_2 \\ G_3 & G_2 \end{bmatrix}.
\]  

(33)

It is noted that with \( G \) in the form of (33), the matrix \( G_2 \) can be absorbed by introducing \( \tilde{K}_A(i) = G_2 K_A(i), \quad \tilde{K}_B(i) = G_2 K_B(i) \). For design simplicity, we further specify

\[
G_1 = I_n, \quad G_3 = \sigma I_n,
\]  

(34)

where \( \sigma \) is a scalar to be searched.

Now by substituting (32)-(34) into (11), it is seen that (11) and (30) are equivalent. This guarantees the stability and \( H_\infty \) performance bound of the system. We note that since \( G_2 \) is required to be positive-definite, the controller gains can be calculated via (31). This completes the proof.

Remark 5: We note that in Theorem 2, we introduce four tuning parameters \( q_1, q_2, q_3 \) and \( \sigma \) to provide extra freedom in the solution space and to obtain less conservative results. When these parameters are available, (30) is a strict LMI problem which can be handled by standard LMI solvers [39]. Moreover, non-gradient based optimizers such as MATLAB fminsearch can be exploited for tuning \( q_1, q_2, q_3 \) and \( \sigma \). See [40] for similar application of fminsearch for robust controller designs.

**IV. APPLICATION TO A SUSPENSION SYSTEM**

In this section, the proposed controller design is applied to a semi-active suspension system which is monitored and controlled via a cloud-aided network [6].

**A. Cloud-based suspension control framework**

For suspension control problems, one promising solution is to take into account the real-time road profile information as external disturbances, based on which controllers are developed such that the optimal performance in terms of handling and comfort can be achieved. It is acknowledged that onboard computation units embedded in electronic control units (ECUs) of the vehicles have limited data storage and computation resources. Alternatively, the Vehicle-to-Cloud-to-Vehicle (V2C2V) framework, which is featured by high computational capacities, provides a natural way to address such problems. A V2C2V suspension control system is developed and the schematic is presented as in Figure 1.
In this architecture, “road info” contains uneven road information (e.g., road potholes) that may directly affect the travel performance of the vehicles and the control actions. Real-time information on the vehicle location (i.e., “GPS info”), car velocity and other related measurements are transmitted from the vehicles to a cloud-aided agent, where road profile information is stored and control actions are determined. When an updated control signal is generated, it is sent back to the corresponding suspension actuator via a wireless communication system. Based on the obtained control commands, the actuators correspondingly change the magneto-rheologic (MR) fluid viscosity in MR dampers or change orifice of a current-controlled value in Telescopic-Hydraulic dampers for damping ratio adjustment to improve the handling and comfort performance as well as to guarantee the safety for the passengers [41]. Since the communication performance varies significantly depending on vehicle locations, communication system conditions, etc., an MCCs scheme with channel switching is deployed for communication in order to improve data transmission efficiency and reliability.

B. Modeling of the suspension system

Quarter-car models are frequently used for suspension and chassis designs because they are able to capture significant features of a typical car model [42], [43]. In this paper, the suspension system that serves as a quarter-car model with 2 degrees of freedom is employed. A schematic of the suspension system that serves as a quarter-car model features of a typical car model [42], [43]. In this paper, data transmission efficiency and reliability.

![Remote agent](Image1)

![Vehicle](Image2)

**Fig. 1.** A schematic of the cloud-aided suspension control system

**Fig. 2.** Schematic of the suspension system

The tire is approximated as a spring with stiffness \( k_s \) and mass \( M_s \), the spring and shocker absorber that are subject to adjustable damping ratio and are used to connect the sprung (body unit) and the unsprung (wheel assembly unit) masses account for the suspension part. The tire is approximated as a spring with stiffness \( k_w \) and damping \( c_s \) and the damping ratio is neglected in the model formulation. The model of the suspension system is constructed as follows [44]:

\[
\begin{align*}
\dot{x}_1 &= x_2 - w - \dot{r}_0 \\
M_s \dot{x}_2 &= -k_w x_1 + k_s x_3 + c_s (x_4 - x_2) + u \\
\dot{x}_3 &= x_4 - x_2 \\
M_s \dot{x}_4 &= -k_w x_3 - c_s (x_4 - x_2) - u
\end{align*}
\]

where \( x_1 \) denotes the tire deflection from the equilibrium point; \( x_2 \) denotes the unsprung mass velocity; \( x_3 \) represents the suspension deflection from the equilibrium point; \( x_4 \) is the sprung mass velocity. Two kinds of disturbances are considered in the simulation. \( w \) denotes the unknown disturbances caused by inaccurate GPS localization as well as inaccurate sensor measurements from the vehicles, while \( \dot{r}_0 \), which can be retrieved from the remote agent via the communication channels, is used to model the road profile information that characterizes the uneven road conditions. \( c_s \) is the damping constant and \( u \) is adjustable damper force as the controlled input; \( k_s \) and \( k_w \) denote suspension stiffness and tire stiffness, respectively.

Let us consider state vector \( x = [x_1 \ x_2 \ x_3 \ x_4]^T \), a compact form of the system model is obtained as:

\[
\dot{x}(t) = (A + \Delta A(t)) x(t) + (B + \Delta B(t)) u(t) + B_w (w(t) + \dot{r}_0(t))
\]

where

\[
A = \begin{bmatrix}
0 & 1 & 0 & 0 \\
-k_{ws} & -c_s & k_w & c_s \\
0 & -1 & 0 & -c_s \\
0 & -k_s & 0 & -c_s
\end{bmatrix},
B = \begin{bmatrix}
0 \\
1/M_{us} \\
0 \\
1/M_s
\end{bmatrix}
\]

\[
\Delta A(t) = 0.05 \sin t \cdot A,
\Delta B(t) = 0.05 \cos t \cdot B,
B_w = [-1 \ 0 \ 0 \ 0]^T
\]

the parameters of which are given in Table I.

From a practical perspective, suspension deflection \( x_3 \) and body velocity \( x_4 \) are measurable, while tire deflection \( x_1 \) and vertical wheel velocity \( x_2 \) can be hardly measured. In addition, the objective is to improve vehicle performance in terms of handling, comfort and safety, which can be realized by minimizing tire deflection \( x_1 \) and suspension deflection \( x_3 \) via adjusting the damper force. Based on above considerations,
we determine the matrices of the output measurements and the controlled outputs as follows:

\[
\begin{align*}
C &= \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \\
D &= \begin{bmatrix} 0.01 \\ 0.01 \end{bmatrix}, \\
L_0 &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \\
L_1 &= \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}
\end{align*}
\]

C. Road profile modeling

Accurate information in terms of road profile is of vital importance for achieving optimal control performance. Road profile information can be downloaded from vendors that have collected the information previously using accelerometers, laser height sensor and distance measuring instruments, etc.

In practice, the information with respect to road conditions vastly varies depending on many external factors, thus can be approximated or described by different dynamic models under different conditions. For simulation purposes, a road segment over a period of 10s is modeled as:

\[
\dot{r}_0 = \begin{cases} 
0.4 \cdot \cos 2\pi t & 0.3s \geq t \geq 0.8s \\
0.05 \cdot \sin 2\pi t & 6.4s \geq t \geq 6.8s \\
0 & \\
\end{cases} 
\]

D. Simulation settings and results

We consider three independent communication channels subject to Markovian channel switching, which is governed by the following infinitesimal generator,

\[
\Lambda = \begin{bmatrix} -3 & 4 & -1 \\ 2 & -5 & 3 \\ 2 & 5 & -7 \end{bmatrix}.
\]

It is assumed that the packet arrival rates of the three channels from sensors to controllers implemented in the remote agent are subject to \(\Theta_1^{2c} = \text{diag} \{0.96, 0.96\}\), \(\Theta_2^{2c} = \text{diag} \{0.92, 0.92\}\) and \(\Theta_3^{2c} = \text{diag} \{0.97, 0.97\}\), respectively. The packet arrival rates of the three channels from the controllers to the actuator are subject to \(\Theta_1^{2a} = 0.98\), \(\Theta_2^{2a} = 0.95\) and \(\Theta_3^{2a} = 0.99\), respectively. The time-varying communication delays for each communication channel are constrained by the following characteristics: \(\tau_1 = 0.30\), \(\tau_1 = 0.085\), \(\tau_2 = 0.35\), \(\tau_2 = 0.10\), \(\tau_3 = 0.33\), \(\tau_3 = 0.075\), \(d = 0.5\). Without loss of generality, we assume that the upper and lower delay bounds account for both sensor-to-controller delays and controller-to-actuator delays for each channel (i.e., \(\tau_i^{2c} = \tau_i^{2a}\), \(i = 1, 2, 3\)) for analytical convenience.

The overall time-varying communication delays of different channels from sensors to actuators via controllers embedded in the remote agent are presented in Figure 3. A minimum-delay channel scheduler is utilized, that is, the scheduler selects the channel with the minimum delay for data transmission, which is shown in solid black line in Figure 3. The channel switching signal is given in Figure 4. We note that in this simulation, it is assumed that the number sequence of the channels with minimum delays is governed by a Markov chain such that the channel switching signals are generated based on the infinitesimal generator \(\Lambda\). The simulation results are presented in Figure 5. From this figure, we see that the
proposed controller design method makes the system states that are associated with tire deflection and suspension deflection converge to equilibrium points with existence of GPS localization and road profile disturbances, which is expected to see. Moreover, we compare the performance of the typical single-channel scenarios with that of the MCCs scheme with Markovian channel switching that is subject to a minimum-delay scheduler. In Figure 5, the blue dashed lines indicate the controlled outputs $z_{nc}$ of the MCCs scheme. It is seen that the performance is better than that of the single-channel scenarios, the results of which are shown in red, green and black lines for channel 1, channel 2 and channel 3, respectively. The optimal resilient performance indices of different cases are calculated and given in Table II. From the table we see that the MCCs scheme is able to provide the smallest performance index (0.372) compared to the single-channel communication cases. The results further imply that the control performance of the MCCs scheme with Markovian channel switching can be improved in comparison to conventional strategies where only one communication channel is implemented.

V. CONCLUSIONS

In this paper, a robust controller design method was developed for a class of NCSs with MCCs that are subject to channel switching governed by a Markov chain. Communication delays, packet dropouts and parameter uncertainties have been taken into account within a unified framework. The Lyapunov-Krasovskii method was exploited to derive sufficient conditions for the existence of the controllers and to develop the controller design. The effectiveness and applicability of the proposed methodology for NCSs of MCCs with Markovian channel switching were demonstrated via the application to a cloud-aided semi-active suspension system.

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