Robust H_∞ Control for Networked Systems With Random Packet Losses

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***Abstract*—In this paper, the robust H_∞ control problem is considered for a class of networked systems with random communication packet losses. Because of the limited bandwidth of the channels, such random packet losses could occur, simultaneously, in the communication channels from the sensor to the controller and from the controller to the actuator. The random packet loss is assumed to obey the Bernoulli random binary distribution, and the parameter uncertainties are norm-bounded and enter into both the system and output matrices. In the presence of random packet losses, an observer-based feedback controller is designed to robustly exponentially stabilize the networked system in the sense of mean square and also achieve the prescribed H_∞ disturbance-rejection-attenuation level. Both the stability-analysis and controller-synthesis problems are thoroughly investigated. It is shown that the controller-design problem under consideration is solvable if certain linear matrix inequalities (LMIs) are feasible. A simulation example is exploited to demonstrate the effectiveness of the proposed LMI approach.**

***Index Terms*—H_∞ control, linear matrix inequality (LMI), networked systems, random packet loss, stochastic stability.**

I. Introduction

SINCE NETWORKS may greatly decrease the hardwiring, the cost of installation and implementation, in recent years, of networked control systems (NCSs) have found successful applications in a wide range of areas such as industrial automation, distributed/mobile communication, unmanned vehicles, and Internet-based control. While NCSs have received increasing research attention, they have also given rise to new challenges due to inherent network-limited bandwidth. Among all the challenges that emerged, the intermittent data packet losses and the signal-transmission delay are known to be two of the main causes for the performance deterioration or even the instability of the controlled networked system. Hence, it is not surprising that, in the past few years, the control problem of networked systems with packet losses (or data missing) and time-delays has attracted considerable research interests (see, e.g., [1], [7], [10], [11], [14], [26]–[29], and references therein). This paper is concerned with the impact of packet losses (or data missing) on the design of NCSs.

In the literature, there have been basically three approaches for modeling the packet-loss phenomenon in the NCSs. An arguably popular approach is to view the packet loss as a binary switching sequence that is specified by a conditional probability distribution in the signal-transmission channel. The binary switching sequence obeys a Bernoulli distributed white sequence taking on values of zero and one with certain probability [13]. Recently, there have been some results published on such a model (see, e.g., [19], [21]–[24], and references therein). The second approach is to use a discrete-time linear system with Markovian jumping parameter to represent random packet-loss model for the network. A few control methodologies have been developed for such a system [12], [18]. The third approach is to replace the packet losses by zeros and then construct an incompleteness matrix in the measurement. Such an idea has been used [16], [17] to deal with the robust filtering problems, with data missing or packet losses.

It should be pointed out that, in almost all the existing literature, it has been implicitly assumed that the packet-loss problem occurs only in the channel from the sensor to the controller. Another typical kind of packet losses, which happen in the channel from the controller to the actuator, has not been adequately studied. In addition, in the presence of packet losses, the system-performance requirements such as robustness and disturbance rejection attenuation have not yet gained sufficient research attention. The purpose of this paper is, therefore, to shorten the aforementioned gap.

In this paper, we aim to tackle the robust H_∞ control problem for a class of NCSs with both random sensor-to-controller and controller-to-actuator packet losses. These random packet losses are modeled as a linear function of the stochastic variable satisfying Bernoulli random binary distribution. An observer-based controller is designed such that the closed-loop NCS is robustly stochastically exponentially stable, and the prescribed H_∞ disturbance-rejection-attenuation performance is also achieved. Both the stability-analysis and controller-synthesis problems are thoroughly investigated. It is shown that the controller-design problem under consideration is solvable if certain linear matrix inequalities (LMIs) are feasible. A simulation example is exploited to demonstrate the effectiveness of the proposed LMI approach.

Notation. The notation $X \geq Y$ (respectively, $X > Y$), where X and Y are symmetric matrices, means that $X - Y$

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is positive semidefinite (respectively, positive definite). $\mathbb{E}\{x\}$ stands for the expectation of the stochastic variable x. $\text{Prob}\{\cdot\}$ means the occurrence probability of the event "$\cdot$." If A is a matrix, $\lambda_{\max}(A)$ [respectively, $\lambda_{\min}(A)$] means the largest (respectively, smallest) eigenvalue of A. $l_2[0,\infty)$ is the space of square integrable vectors, and $\mathbb{I}^+$ is the set of positive integer. In symmetric block matrices, "$*$" is used as an ellipsis for terms induced by symmetry.

II. Problem Formulation and Preliminaries

There are different ways to define note Quality-of-Service (QoS) for NCS [4]. In this paper, we take into account two of the most popular QoS measures: 1) the point-to-point network allowable data-dropout rate that is used to indicate the probability of data packet dropout in data transmission and 2) the point-to-point network throughput that is used to indicate how fast the signal can be sampled and sent as a packet through the network. Another important QoS measure, maximum allowable equivalent delay bound, will be investigated in our future work.

To the NCS considered in this paper, the sampling period h and the data-dropout rate ρ determine the control performance. We assume that the data are single-packet transmitted, different data packet has the same length L, and the network throughput distributed by packet scheduler is Q_{i_k} in $t \in [i_k h, i_{k+1}h)$. The network allowable data-dropout rate is related with the packet scheduler, backlog controller, and algorithm complex of loss dropper policy. As will be seen later, we will use different data-dropout rates (measurement missing probability) to quantify the random packet losses in the sensor-to-controller channel and the controller-to-actuator channel. On the other hand, the sampling period h is decided by network throughput Q_{i_k} and the number of sensors. Small sampling period can have good control performance but can induce network congest and improve the data-dropout rate.

Since there has been a rich body of literature studying appropriate sampling method [9], in this paper, we assume that a sampled-data model can be obtained through online measurement such as sending probing data packet to measure network characteristics and QoS scheduling. Consider the following NCS after sampling:

$$\begin{cases} x_{k+1} = (A+\Delta A)x_k + B_2 u_k + B_1 w_k \\ z_k = (C_1 + \Delta C)x_k + D_1 w_k \end{cases} \tag{1}$$

where $x_k \in \mathbb{R}^n$ is the state, $u_k \in \mathbb{R}^m$ is the control input, $z_k \in \mathbb{R}^r$ is the controlled output, $w_k \in \mathbb{R}^q$ is the disturbance input belonging to $l_2[0,\infty)$, and A, B_1, B_2, C_1, and D_1 are known real matrices with appropriate dimensions. The parameter uncertainties ΔA and ΔC are assumed to be of the form

$$\begin{bmatrix} \Delta A \\ \Delta C \end{bmatrix} = \begin{bmatrix} H_1 \\ H_2 \end{bmatrix} F_k E \tag{2}$$

where H_1, H_2, and E are known real constant matrices of appropriate dimensions, and F_k represents an unknown real-valued time-varying matrix satisfying $F_k F_k^T \le I$.

Remark 1: As discussed before, networked systems are becoming more and more popular for the reason that they have several advantages over traditional systems, such as low cost, reduced weight and power requirements, simple installation and maintenance, and high reliability. If network media is introduced to control-system design, the data-packet-dropout phenomenon, which appears in a typical network environment, will naturally induce missing observations, which makes the controller-design problem much more involved.

In this paper, the measurement with random communication packet loss is described by

$$y_k = \alpha_k C_2 x_k + D_2 w_k \tag{3}$$

where the stochastic variable $\alpha_k \in \mathbb{R}$ is a Bernoulli distributed white sequence with

$$\text{Prob}\{\alpha_k = 1\} = \mathbb{E}\{\alpha_k\} := \bar{\alpha} \tag{4}$$

$$\text{Prob}\{\alpha_k = 0\} = 1 - \mathbb{E}\{\alpha_k\} := 1 - \bar{\alpha}. \tag{5}$$

Here, $y_k \in \mathbb{R}^p$ is the measured output vector, and C_2 and D_2 are known real matrices with appropriate dimensions.

The dynamic observer-based control scheme for the system (1) is described by

$$\begin{cases} \hat{x}_{k+1} = A\hat{x}_k + B_2 u_k + L(y_k - \bar{\alpha} C_2 \hat{x}_k) \\ \hat{u}_k = -K\hat{x}_k \\ u_k = \beta_k \hat{u}_k \end{cases} \tag{6}$$

where $\hat{x}_k \in \mathbb{R}^n$ is the state estimate of the system (1), $\hat{u}_k \in \mathbb{R}^m$ is the control input without transmission missing, and $L \in \mathbb{R}^{n\times p}$ and $K \in \mathbb{R}^{m\times n}$ are the observer and controller gains, respectively. The stochastic variable $\beta_k \in \mathbb{R}$, mutually independent of α_k, is also a Bernoulli distributed white sequence with

$$\text{Prob}\{\beta_k = 1\} = \mathbb{E}\{\beta_k\} := \bar{\beta} \tag{7}$$

$$\text{Prob}\{\beta_k = 0\} = 1 - \mathbb{E}\{\beta_k\} := 1 - \bar{\beta}. \tag{8}$$

Remark 2: It can be noticed from (3) and (6) that the independent Bernoulli distributed white sequences α_k and β_k are introduced to reflect the random packet losses in, respectively, the sensor-to-controller and controller-to-actuator channels. The random packet-loss mode in the sensor output (3) was first introduced in the study in [13] and has been subsequently studied in many recent NCS papers (see, e.g., [19], [21]–[24]). However, very few papers have considered the packet-loss problems in both sensor-to-controller and controller-to-actuator channels, despite its significance in the current networked systems.

Let the estimation error be

$$e_k := x_k - \hat{x}_k. \tag{9}$$

The closed-loop system can be obtained by substituting (3) and (6) into (1) and (9)

$$\begin{cases} x_{k+1} = (A + \Delta A - \bar{\beta} B_2 K)x_k + \bar{\beta} B_2 K e_k + (\beta_k - \bar{\beta}) \\ \qquad \times B_2 K x_k + (\beta_k - \bar{\beta}) B_2 K e_k + B_1 w_k \\ e_{k+1} = \Delta A x_k + (A - \bar{\alpha} L C_2) e_k - (\alpha_k - \bar{\alpha}) L C_2 x_k \\ \qquad + (B_1 - L D_2) w_k \end{cases} \tag{10}$$

or in a compact form as follows:

$$\eta_{k+1} = \bar{A}\eta_k + \epsilon_k \tilde{A}\eta_k + \bar{B} w_k \tag{11}$$

where

$$\eta_k = \begin{bmatrix} x_k \\ e_k \end{bmatrix}$$

$$\bar{A} = \begin{bmatrix} A + \Delta A + \bar{\beta} B_2 K & -\bar{\beta} B_2 K \\ \Delta A & A - \bar{\alpha} L C_2 \end{bmatrix}$$

$$\epsilon_k = \begin{bmatrix} (\beta_k - \bar{\beta}) I & 0 \\ 0 & (\alpha_k - \bar{\alpha}) I \end{bmatrix}$$

$$\tilde{A} = \begin{bmatrix} B_2 K & B_2 K \\ L C_2 & 0 \end{bmatrix}$$

$$\bar{B} = \begin{bmatrix} B_1 \\ B_1 - L D_2 \end{bmatrix}.$$

It should be pointed out that in the closed-loop system (11), there appear stochastic quantities α_k and β_k. This differs from the traditional deterministic systems without random packet losses. To deal with the stochastic parameter system (11), we are now in a position to introduce the concept of stochastic stability in the mean-square sense.

Definition 1: The closed-loop system (11) is said to be exponentially mean-square stable if, with $w_k = 0$, there exist constants $\phi > 0$ and $\tau \in (0, 1)$, such that

$$\mathbb{E}\left\{\|\eta_k\|^2\right\} \leq \phi \tau^k \mathbb{E}\left\{\|\eta_0\|^2\right\}, \quad \text{for all } \eta_0 \in \mathbb{R}^n, \quad k \in \mathbb{I}^+. \tag{12}$$

In this paper, we aim to design the controller (6) for the system (1), such that, in the presence of random packet losses, the closed-loop system (11) is exponentially mean-square stable, and the H_∞ performance constraint is satisfied. More specifically, we like to design a controller such that the closed-loop system satisfies the following two performance requirements (Q1) and (Q2).

(Q1) The closed-loop system (11) is exponentially mean-square stable.

(Q2) Under the zero-initial condition, the controlled output z_k satisfies

$$\sum_{k=0}^{\infty} \mathbb{E}\left\{\|z_k\|^2\right\} < \gamma^2 \sum_{k=0}^{\infty} \mathbb{E}\left\{\|w_k\|^2\right\} \tag{13}$$

for all nonzero w_k, where $\gamma > 0$ is a prescribed scalar.

III. Main Results and Proofs

Throughout this paper, without loss of generality, we will make the following assumption for technical convenience.

Assumption 1: The matrix B_2 is of full-column rank, i.e., $\mathrm{rank}(B_2) = m$.

For the matrix B_2 of full-column rank, there always exist two orthogonal matrices $U \in \mathbb{R}^{n \times n}$ and $V \in \mathbb{R}^{m \times m}$, such that

$$\tilde{B}_2 = U B_2 V = \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} B_2 V = \begin{bmatrix} \Sigma \\ 0 \end{bmatrix} \tag{14}$$

where $U_1 \in \mathbb{R}^{m \times n}$ and $U_2 \in \mathbb{R}^{(n-m) \times n}$ and $\Sigma = \mathrm{diag}\{\sigma_1, \sigma_2, \ldots, \sigma_m\}$, where σ_i $(i = 1, 2, \ldots, m)$ are nonzero singular values of B_2.

In the derivation of our main results, we will need the following three lemmas.

Lemma 1: Ho and Lu [8, Lemma 3]. For the matrix $B_2 \in \mathbb{R}^{n \times m}$ that is of full-column rank, if matrix P_1 is of the following structure:

$$P_1 = U^{\mathrm{T}} \begin{bmatrix} P_{11} & 0 \\ 0 & P_{12} \end{bmatrix} U = U_1^{\mathrm{T}} P_{11} U_1 + U_2^{\mathrm{T}} P_{22} U_2 \tag{15}$$

where $P_{11} \in \mathbb{R}^{m \times m} > 0$, and $P_{22} \in \mathbb{R}^{(n-m) \times (n-m)} > 0$, and U_1 and U_2 are defined in (14), then there exists a nonsingular matrix $P \in \mathbb{R}^{m \times m}$, such that $B_2 P = P_1 B_2$.

Remark 3: The purpose of Lemma 1 is to find a solution of $B_2 P = P_1 B_2$ for P, which will later facilitate our development of the LMI approach to the controller design. The assumption of B, being a full-column rank, is just for presentation convenience, which does not lose any generality, as we can always conduct congruence transformation on B. If the condition (15) holds, then P exists, but it may not unique unless B is square and nonsingular.

Lemma 2: (S-procedure) [3], [25]. Let $M = M^{\mathrm{T}}$ and H and E be real matrices of appropriate dimensions with F satisfying $FF^{\mathrm{T}} < I$, then $M + HFE + E^{\mathrm{T}} F^{\mathrm{T}} H^{\mathrm{T}} < 0$, if and only if there exists a positive scalar $\varepsilon > 0$, such that

$$M + \frac{1}{\varepsilon} H H^{\mathrm{T}} + \varepsilon E^{\mathrm{T}} E < 0 \tag{16}$$

or equivalently

$$\begin{bmatrix} M & H & \varepsilon E^{\mathrm{T}} \\ H^{\mathrm{T}} & -\varepsilon I & 0 \\ \varepsilon E & 0 & -\varepsilon I \end{bmatrix} < 0. \tag{17}$$

Lemma 3: Tarn and Rasis [20, Theorem 2]. Let $V(\eta_k)$ be a Lyapunov functional. If there exist real scalars $\lambda \geq 0$, $\mu > 0$, $\nu > 0$, and $0 < \psi < 1$, such that

$$\mu \|\eta_k\|^2 \leq V(\eta_k) \leq \nu \|\eta_k\|^2 \tag{18}$$

and

$$\mathbb{E}\left\{V(\eta_{k+1}) | \eta_k\right\} - V(\eta_k) \leq \lambda - \psi V(\eta_k) \tag{19}$$

then the sequence η_k satisfies

$$\mathbb{E}\left\{\|\eta_k\|^2\right\} \leq \frac{\nu}{\mu} \|\eta_0\|^2 (1 - \psi)^k + \frac{\lambda}{\mu \psi}. \tag{20}$$

In the following theorem, a sufficient condition is established for the exponentially mean-square stability of the closed-loop system (11).

Theorem 1: Suppose that both the controller gain matrix K and the observer gain matrix L are given. The closed-loop system (11) is exponentially mean-square stable if there exist positive definite matrices P_1 and P_2 satisfying

$$\begin{bmatrix} A+\Delta A-\bar{\beta}B_2K & \bar{\beta}B_2K \\ \Delta A & A-\bar{\alpha}LC_2 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} \times \begin{bmatrix} A+\Delta A-\bar{\beta}B_2K & \bar{\beta}B_2K \\ \Delta A & A-\bar{\alpha}LC_2 \end{bmatrix} + \begin{bmatrix} B_2K & B_2K \\ LC_2 & 0 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \beta_1^2 P_1 & 0 \\ 0 & \alpha_1^2 P_2 \end{bmatrix} \times \begin{bmatrix} B_2K & B_2K \\ LC_2 & 0 \end{bmatrix} - \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} < 0 \tag{21}$$

where $\alpha_1 = [(1-\bar{\alpha})\bar{\alpha}]^{1/2}$, and $\beta_1 = [(1-\bar{\beta})\bar{\beta}]^{1/2}$.

Proof: Define a Lyapunov functional

$$V_k = x_k^{\mathrm{T}} P_1 x_k + e_k^{\mathrm{T}} P_2 e_k \tag{22}$$

where P_1 and P_2 are positive definite solutions to (21). It follows from (10) that

$$\begin{aligned} &\mathbb{E}\{V_{k+1}|x_k,\ldots,x_0,e_k,\ldots,e_0\} - V_k \\ &= \mathbb{E}\left\{x_{k+1}^{\mathrm{T}} P_1 x_{k+1} + e_{k+1}^{\mathrm{T}} P_2 e_{k+1}\right\} - x_k^{\mathrm{T}} P_1 x_k - e_k^{\mathrm{T}} P_2 e_k \\ &= \mathbb{E}\Big\{\big[(A+\Delta A-\bar{\beta}B_2K)x_k + \bar{\beta}B_2Ke_k \\ &\qquad + (\beta_k-\bar{\beta})B_2Kx_k + (\beta_k-\bar{\beta})B_2Ke_k\big]^{\mathrm{T}} \\ &\quad \times P_1\big[(A+\Delta A-\bar{\beta}B_2K)x_k + \bar{\beta}B_2Ke_k + (\beta_k-\bar{\beta}) \\ &\qquad \times B_2Kx_k + (\beta_k-\bar{\beta})B_2Ke_k\big] \\ &\quad + [\Delta A x_k + (A-\bar{\alpha}LC_2)e_k - (\alpha_k-\bar{\alpha})LC_2x_k]^{\mathrm{T}} \\ &\quad \times P_2[\Delta A x_k + (A-\bar{\alpha}LC_2)e_k - (\alpha_k-\bar{\alpha})LC_2x_k]\Big\} \\ &\quad - x_k^{\mathrm{T}} P_1 x_k - e_k^{\mathrm{T}} P_2 e_k. \end{aligned} \tag{23}$$

Noting that $\mathbb{E}\{(\alpha_k-\bar{\alpha})^2\} = (1-\bar{\alpha})\bar{\alpha}$ and $\mathbb{E}\{(\beta_k-\bar{\beta})^2\} = (1-\bar{\beta})\bar{\beta}$, we have

$$\begin{aligned} &\mathbb{E}\{V_{k+1}|x_k,\ldots,x_0,e_k,\ldots,e_0\} - V_k \\ &= \big[(A+\Delta A-\bar{\beta}B_2K)x_k + \bar{\beta}B_2Ke_k\big]^{\mathrm{T}} \\ &\quad \times P_1\big[(A+\Delta A-\bar{\beta}B_2K)x_k + \bar{\beta}B_2Ke_k\big] \\ &\quad + [\Delta A x_k + (A-\bar{\alpha}LC_2)e_k]^{\mathrm{T}} P_2 [\Delta A x_k + (A-\bar{\alpha}LC_2)e_k] \\ &\quad + (1-\bar{\beta})\bar{\beta}[B_2Kx_k + B_2Ke_k]^T P_1 [B_2Kx_k + B_2Ke_k] \\ &\quad + (1-\bar{\alpha})\bar{\alpha}x_k^T C_2^T L^T P_2 L C_2 x_k - x_k^T P_1 x_k - e_k^T P_2 e_k \\ &= \eta_k^T \Lambda \eta_k \end{aligned} \tag{24}$$

where

$$\Lambda := A_1^{\mathrm{T}} P_1 A_1 + A_2^{\mathrm{T}} P_2 A_2 + \begin{bmatrix} B_2K & B_2K \\ LC_2 & 0 \end{bmatrix}^{\mathrm{T}} \times \begin{bmatrix} \beta_1^2 P_1 & 0 \\ 0 & \alpha_1^2 P_2 \end{bmatrix} \begin{bmatrix} B_2K & B_2K \\ LC_2 & 0 \end{bmatrix} - \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} \tag{25}$$

and

$$A_1 := [A+\Delta A-\bar{\beta}B_2K \quad \bar{\beta}B_2K] \tag{26}$$

$$A_2 := [\Delta A \quad A-\bar{\alpha}LC_2]. \tag{27}$$

It follows from (21) that $\Lambda < 0$, and hence

$$\begin{aligned} &\mathbb{E}\{V_{k+1}|x_k,\ldots,x_0,e_k,\ldots,e_0\} - V_k \\ &= \eta_k^{\mathrm{T}}\Lambda\eta_k \le -\lambda_{\min}(-\Lambda)\eta_k^T\eta_k < -\alpha\eta_k^{\mathrm{T}}\eta_k \end{aligned} \tag{28}$$

where

$$0 < \alpha < \min\{\lambda_{\min}(-\Lambda), \sigma\} \qquad \sigma := \max\{\lambda_{\max}(P_1), \lambda_{\max}(P_2)\}. \tag{29}$$

From (28), we have

$$\begin{aligned} &\mathbb{E}\{V_{k+1}|x_k,\ldots,x_0,e_k,\ldots,e_0\} \\ &\quad - V_k < -\alpha\eta_k^T\eta_k < -\frac{\alpha}{\sigma}V_k := -\psi V_k. \end{aligned} \tag{30}$$

Therefore, by Definition 1, it can be verified from Lemma 3 that the closed-loop system (11) is exponentially mean-square stable. This completes the proof. ■

Next, we will continue to explore the sufficient conditions for achieving the robust H_∞ performance constraints. Note that, in the stochastic setting, we use the expression (13) to quantify the H_∞ performances where the expectation operator is utilized on both the controlled output and the disturbance input (see [2] for more details).

Theorem 2: Given a scalar $\gamma > 0$. The system (11) is robustly exponentially mean-square stable and the H_∞ norm constraint (13) is achieved for all nonzero w_k, if there exist positive-definite matrices P_1 and P_2, a positive real scalar $\epsilon > 0$, and real matrices K and L satisfying (31), shown at the bottom of the page.

$$\begin{bmatrix} -P_1 & * & * & * & * & * & * & * & * & * \\ 0 & -P_2 & * & * & * & * & * & * & * & * \\ 0 & 0 & -\gamma^2 I & * & * & * & * & * & * & * \\ P_1A-\bar{\beta}P_1B_2K & \bar{\beta}P_1B_2K & P_1B_1 & -P_1 & * & * & * & * & * & * \\ 0 & P_2A-\bar{\alpha}P_2LC_2 & P_2B_1-P_2LD_2 & 0 & -P_2 & * & * & * & * & * \\ C_1 & 0 & D_1 & 0 & 0 & -I & * & * & * & * \\ \beta_1P_1B_2K & \beta_1P_1B_2K & 0 & 0 & 0 & 0 & -P_1 & * & * & * \\ \alpha_1P_2LC_2 & 0 & 0 & 0 & 0 & 0 & 0 & -P_2 & * & * \\ 0 & 0 & 0 & H_1^TP_1 & H_1^TP_2 & H_2^T & 0 & 0 & -\epsilon I & * \\ \epsilon E & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\varepsilon I \end{bmatrix} < 0 \tag{31}$$

Proof: We first show that there exists a positive scalar $\varepsilon > 0$, such that (31) holds if and only if the inequality (32) holds, shown near the bottom of the page.

The condition (32) can be rewritten in the form of (16) as follows:

$$\hat{M} + \hat{H}F\hat{E} + \hat{E}^{\mathrm{T}}F^{\mathrm{T}}\hat{H}^{\mathrm{T}} < 0 \tag{33}$$

where we have the expression shown at the bottom of the page.

Applying Lemma 2 to (33), we know that (32) holds if and only if there exists a positive scalar parameter ε, such that LMI (34) holds, shown at the bottom of the page. Using Schur complement, we can easily see that (34) implies (31). Therefore, from the condition of this theorem, we can conclude that (32) is true.

Now, it is clear from Theorem 1 that the system (11) is exponentially mean-square stable since (32) results in (21). Now, for any nonzero w_k, it follows from (10) and (24) that

$$\begin{aligned}
&\mathbb{E}\{V_{k+1}\} - \mathbb{E}\{V_k\} + \mathbb{E}\{z_k^{\mathrm{T}} z_k\} - \gamma^2\mathbb{E}\{w_k^{\mathrm{T}} w_k\} \\
&\quad = \mathbb{E}\Big\{\big[(A + \Delta A - \bar{\beta}B_2K)x_k + \bar{\beta}B_2Ke_k \\
&\qquad\qquad + (\beta_k - \bar{\beta})B_2Kx_k + (\beta_k - \bar{\beta})B_2Ke_k + B_1w_k\big]^{\mathrm{T}} \\
&\qquad \times P_1\big[(A + \Delta A - \bar{\beta}B_2K)x_k + \bar{\beta}B_2Ke_k \\
&\qquad\qquad + (\beta_k - \bar{\beta})B_2Kx_k + (\beta_k - \bar{\beta})B_2Ke_k + B_1w_k\big] \\
&\qquad + [\Delta Ax_k + (A - \bar{\alpha}LC_2)e_k \\
&\qquad\quad - (\alpha_k - \bar{\alpha})LC_2x_k + (B_1 - LD_2)w_k]^{\mathrm{T}} \\
&\qquad \times P_2[\Delta Ax_k + (A - \bar{\alpha}LC_2)e_k - (\alpha_k - \bar{\alpha}) \\
&\qquad\quad \times LC_2x_k + (B_1 - LD_2)w_k] \\
&\qquad - x_k^{\mathrm{T}}P_1x_k - e_k^{\mathrm{T}}P_2e_k + \big[(C_1 + \Delta C)x_k + D_1w_k\big]^{\mathrm{T}} \\
&\qquad \times \left[(C_1 + \Delta C)x_k + D_1w_k\right] - \gamma^2 w_k^{\mathrm{T}} w_k\Big\} \\
&\quad = \mathbb{E}\left\{\begin{bmatrix}\eta_k \\ w_k\end{bmatrix}^{\mathrm{T}}\begin{bmatrix}\Lambda + \Lambda_1 & \Lambda_2 \\ \Lambda_2^{\mathrm{T}} & \Lambda_3\end{bmatrix}\begin{bmatrix}\eta_k \\ w_k\end{bmatrix}\right\}
\end{aligned} \tag{35}$$

$$\begin{bmatrix}
-P_1 & * & * & * & * & * & * & * \\
0 & -P_2 & * & * & * & * & * & * \\
0 & 0 & -\gamma^2 I & * & * & * & * & * \\
A + \Delta A - \bar{\beta}B_2K & \bar{\beta}B_2K & B_1 & -P_1^{-1} & * & * & * & * \\
\Delta A & A - \bar{\alpha}LC_2 & B_1 - LD_2 & 0 & -P_2^{-1} & * & * & * \\
C_1 + \Delta C & 0 & D_1 & 0 & 0 & -I & * & * \\
\beta_1 B_2K & \beta_1 B_2K & 0 & 0 & 0 & 0 & -P_1^{-1} & * \\
\alpha_1 LC_2 & 0 & 0 & 0 & 0 & 0 & 0 & -P_2^{-1}
\end{bmatrix} < 0 \tag{32}$$

$$\hat{M} = \begin{bmatrix}
-P_1 & * & * & * & * & * & * & * \\
0 & -P_2 & * & * & * & * & * & * \\
0 & 0 & -\gamma^2 I & * & * & * & * & * \\
A - \bar{\beta}B_2K & \bar{\beta}B_2K & B_1 & -P_1^{-1} & * & * & * & * \\
0 & A - \bar{\alpha}LC_2 & B_1 - LD_2 & 0 & -P_2^{-1} & * & * & * \\
C_1 & 0 & D_1 & 0 & 0 & -I & * & * \\
\beta_1 B_2K & \beta_1 B_2K & 0 & 0 & 0 & 0 & -P_1^{-1} & * \\
\alpha_1 LC_2 & 0 & 0 & 0 & 0 & 0 & 0 & -P_2^{-1}
\end{bmatrix}$$

$$\hat{H} = \begin{bmatrix}0 & 0 & 0 & H_1^{\mathrm{T}} & H_1^{\mathrm{T}} & H_2^{\mathrm{T}} & 0 & 0\end{bmatrix}^{\mathrm{T}}$$

$$\hat{E} = \begin{bmatrix}E & 0 & 0 & 0 & 0 & 0 & 0 & 0\end{bmatrix}$$

$$\begin{bmatrix}
-P_1 & * & * & * & * & * & * & * & * & * \\
0 & -P_2 & * & * & * & * & * & * & * & * \\
0 & 0 & -\gamma^2 I & * & * & * & * & * & * & * \\
A - \bar{\beta}B_2K & \bar{\beta}B_2K & B_1 & -P_1^{-1} & * & * & * & * & * & * \\
0 & A - \bar{\alpha}LC_2 & B_1 - LD_2 & 0 & -P_2^{-1} & * & * & * & * & * \\
C_1 & 0 & D_1 & 0 & 0 & -I & * & * & * & * \\
\beta_1 B_2K & \beta_1 B_2K & 0 & 0 & 0 & 0 & -P_1^{-1} & * & * & * \\
\alpha_1 LC_2 & 0 & 0 & 0 & 0 & 0 & 0 & -P_2^{-1} & * & * \\
0 & 0 & 0 & H_1^{\mathrm{T}} & H_1^{\mathrm{T}} & H_2^{\mathrm{T}} & 0 & 0 & -\epsilon I & * \\
\epsilon E & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\varepsilon I
\end{bmatrix} < 0 \tag{34}$$

where

$$\Lambda_1 := [\,C_1+\Delta C \quad 0\,]^{\mathrm{T}}[\,C_1+\Delta C \quad 0\,] \tag{36}$$

$$\Lambda_2 := A_1^{\mathrm{T}}P_1B_1 + A_2^{\mathrm{T}}P_2(B_1 - LD_2) + A_3^{\mathrm{T}}D_1 \tag{37}$$

$$\Lambda_3 := B_1^{\mathrm{T}}P_1B_1 + (B_1 - LD_2)^{\mathrm{T}}P_2(B_1 - LD_2) + D_1^{\mathrm{T}}D_1 - \gamma^2 I \tag{38}$$

and Λ is defined in (25).

By Schur complement, (32) implies that

$$\begin{bmatrix} \Lambda + \Lambda_1 & \Lambda_2 \\ \Lambda_2^{\mathrm{T}} & \Lambda_3 \end{bmatrix} < 0 \tag{39}$$

and, therefore, we have from (35) that

$$\mathbb{E}\{V_{k+1}\} - \mathbb{E}\{V_k\} + \mathbb{E}\{z_k^{\mathrm{T}} z_k\} - \gamma^2\mathbb{E}\{w_k^{\mathrm{T}} w_k\} < 0. \tag{40}$$

Summing up (40) from zero to ∞ with respect to k yields

$$\sum_{k=0}^{\infty}\mathbb{E}\{\|z_k\|^2\} < \gamma^2\sum_{k=0}^{\infty}\mathbb{E}\{\|w_k\|^2\} + \mathbb{E}\{V_0\} - \mathbb{E}\{V_\infty\}. \tag{41}$$

Since $\eta_0 = 0$ and the system (11) is exponentially mean-square stable, it is easy to conclude that

$$\sum_{k=0}^{\infty}\mathbb{E}\left\{\|z_k\|^2\right\} < \gamma^2\sum_{k=0}^{\infty}\mathbb{E}\left\{\|w_k\|^2\right\} \tag{42}$$

which means the specified H_∞ norm constraints is achieved, and the proof is then complete. ■

In Theorem 2, the stability analysis has been conducted based on the stochastic Lyapunov stability theory and the S procedure. In the following, we will deal with the controller-design problem and derive the explicit expression of the controller parameters in terms of LMIs. Therefore, the controller design can be easily implemented by using the MATLAB LMI toolbox.

Theorem 3: Given a scalar $\gamma > 0$. The system (11) is exponentially mean-square stable, and the H_∞ norm constraint (13) is achieved for all nonzero w_k if there exist positive-definite matrices $P_{11} \in \mathbb{R}^{m\times m}$, $P_{22} \in \mathbb{R}^{(n-m)\times(n-m)}$, and $P_2 \in \mathbb{R}^{n\times n}$, and real matrices $M \in \mathbb{R}^{m\times n}$ and $N \in \mathbb{R}^{n\times p}$, such that we have (43), shown at the bottom of the page, where $P_1 := U_1^{\mathrm{T}}P_{11}U_1 + U_2^{\mathrm{T}}P_{22}U_2$, and U_1 and U_2 come from (14). Moreover, the controller parameters are given by

$$K = V\Sigma^{-1}P_{11}^{-1}\Sigma V^{\mathrm{T}}M, \qquad L = P_2^{-1}N. \tag{44}$$

Proof: Since there exist $P_{11} > 0$ and $P_{22} > 0$, such that $P_1 = U_1^{\mathrm{T}}P_{11}U_1 + U_2^{\mathrm{T}}P_{22}U_2$, where U_1 and U_2 are defined in (14), it follows from Lemma 1 that there exists a nonsingular matrix $P \in \mathbb{R}^{m\times m}$, such that $B_2P = P_1B_2$. Now, let us calculate such a matrix P from the relation $B_2P = P_1B_2$ as follows:

$$P_1U^{\mathrm{T}}\begin{bmatrix}\Sigma \\ 0\end{bmatrix}V^{\mathrm{T}} = U^{\mathrm{T}}\begin{bmatrix}\Sigma \\ 0\end{bmatrix}V^{\mathrm{T}}P \tag{45}$$

i.e.,

$$U^{\mathrm{T}}\begin{bmatrix}P_{11} & 0 \\ 0 & P_{12}\end{bmatrix}\begin{bmatrix}\Sigma \\ 0\end{bmatrix}V^{\mathrm{T}} = U^{\mathrm{T}}\begin{bmatrix}\Sigma \\ 0\end{bmatrix}V^{\mathrm{T}}P \tag{46}$$

which implies that

$$P = (V^{\mathrm{T}})^{-1}\Sigma^{-1}P_{11}\Sigma V^{\mathrm{T}}. \tag{47}$$

So far, we can conclude from (44) and (47) that

$$B_2P = P_1B_2 \qquad M = PK \qquad N = P_2L \tag{48}$$

and, therefore, it is not difficult to see that (43) is equivalent to (31). The rest of the proof follows from Theorem 2. ■

Remark 4: In Theorem 3, the robust H_∞ control problem is solved for a class of networked systems with random communication packet losses. In the presence of random packet losses, an observer-based feedback controller is designed to robustly exponentially stabilize the networked system in the sense of mean square and also achieve the prescribed H_∞ disturbance-rejection-attenuation level. It is shown that the controller-design problem under consideration is solvable if the LMI (43) is feasible.

As a by-product, we point out that an optimization problem can be formulated as follows: (O1) The optimal H_∞ control problem:

$$\min_{P_{11}>0,P_{22}>0,P_2>0,M,N}\gamma \quad \text{subject to (43).} \tag{49}$$

In the next section, we will illustrate how to solve the optimization problem addressed above.

IV. Simulation Example

The main purpose of an uninterruptable power supply (UPS) is to provide a clean and stable power to a load, regardless of the power-grid conditions, such as blackouts. UPSs have been widely used for office equipment, computers, communication systems, medical/life support, and many other critical

$$\begin{bmatrix}
-P_1 & * & * & * & * & * & * & * & * & * \\
0 & -P_2 & * & * & * & * & * & * & * & * \\
0 & 0 & -\gamma^2 I & * & * & * & * & * & * & * \\
P_1A - \bar{\beta}B_2M & \bar{\beta}B_2M & P_1B_1 & -P_1 & * & * & * & * & * & * \\
0 & P_2A - \bar{\alpha}NC_2 & P_2B_1 - ND_2 & 0 & -P_2 & * & * & * & * & * \\
C_1 & 0 & D_1 & 0 & 0 & -I & * & * & * & * \\
\beta_1B_2M & \beta_1B_2M & 0 & 0 & 0 & 0 & -P_1 & * & * & * \\
\alpha_1NC_2 & 0 & 0 & 0 & 0 & 0 & 0 & -P_2 & * & * \\
0 & 0 & 0 & H_1^{\mathrm{T}}P_1 & H_1^{\mathrm{T}}P_2 & H_2^{\mathrm{T}} & 0 & 0 & -\epsilon I & * \\
\epsilon E & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\varepsilon I
\end{bmatrix} < 0 \tag{43}$$

systems. Recent market requirements include a target expectation for UPS reliability of 99.999% power availability, performance demands of zero switch over time, and complex network connectivity and control methods, such as simple network-management protocol. Therefore, the control problem of network-enabled high-performance UPS has come to play an important role in today's networked world.

In this section, we shall study the networked control problem for the UPS system in order to demonstrate the effectiveness and applicability of the proposed method. Our objective is to control the pulsewidth-modulated inverter, such that the output ac voltage is kept at the desired setting and undistorted, with strong robustness in the presence of disturbance in load. The control signal is transmitted through network cables and, due to the limited bandwidth of the network, the usage of the network may give rise to probabilistic signal losses (packet dropout), which would deteriorate the performance of the networked system. Hence, in the presence of random packet losses, we aim to design an observer-based feedback controller in order to robustly exponentially stabilize the networked system in the sense of mean square and also achieve the prescribed H_∞ disturbance-rejection-attenuation level.

In this application, a UPS with 1 kVA is considered that is described by the discrete-time model matrices with sampling time of 10 ms at half-load operating point as follows [15]:

$$A = \begin{bmatrix} 0.9226 & -0.6330 & 0 \\ 1.0 & 0 & 0 \\ 0 & 1.0 & 0 \end{bmatrix}$$

$$B_1 = \begin{bmatrix} 0.5 \\ 0 \\ 0.2 \end{bmatrix} \quad B_2 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$C_1 = [\,0.1 \quad 0 \quad 0\,] \quad C_2 = [\,23.738 \quad 20.287 \quad 0\,]$$

$$D_1 = 0.1 \quad D_2 = 0.2$$

$$H_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \quad H_2 = 0.2 \quad E = [\,1 \quad 0 \quad 0\,].$$

First, let us design an H_∞ controller (6) with random packet loss with $\bar{\alpha} = \bar{\beta} = 0.95$, such that the H_∞ performance index is minimized. That is, we like to deal with the problem (O1). Solving the optimization problem (49) by using the LMI Toolbox, we obtain that $\gamma_{\min} = 0.4428$ and

$$K = [\,1.1154 \quad -0.6931 \quad 0.0007\,]$$
$$L = [\,0.0251 \quad 0.0294 \quad 0.0145\,]^{\mathrm{T}}.$$

If the initial conditions are set as $x_0 = [1 \quad 0 \quad 0]^{\mathrm{T}}$, $\hat{x}_0 = [0 \quad 0 \quad 0]^{\mathrm{T}}$, and the disturbance input is assumed to be $w_k = 1/k^2$, the simulation result of the state responses are given in Fig. 1, which has verified that our goal is achieved.

Next, let us consider the case when the packet-loss probability is relatively higher. Assuming that $\bar{\alpha} = \bar{\beta} = 0.7$, we are again interested in designing an H_∞ controller (6) that minimizes the H_∞ performance index $\gamma > 0$. Solve the LMI problem (49) to obtain $\gamma_{\min} = 4.9549$ and

$$K = [\,0.7865 \quad -0.7153 \quad 0.1651\,]$$
$$L = [\,0.0069 \quad 0.0205 \quad 0.0178\,]^{\mathrm{T}}.$$

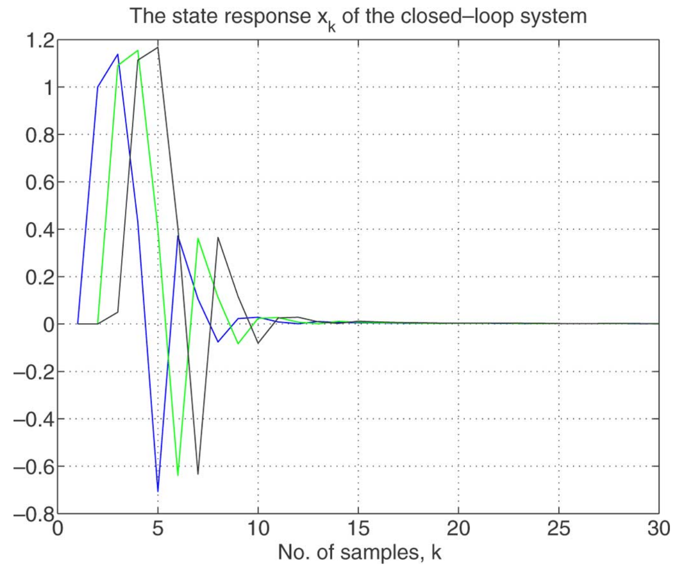

Fig. 1. H_∞ control with $\gamma_{\min} = 0.4428$.

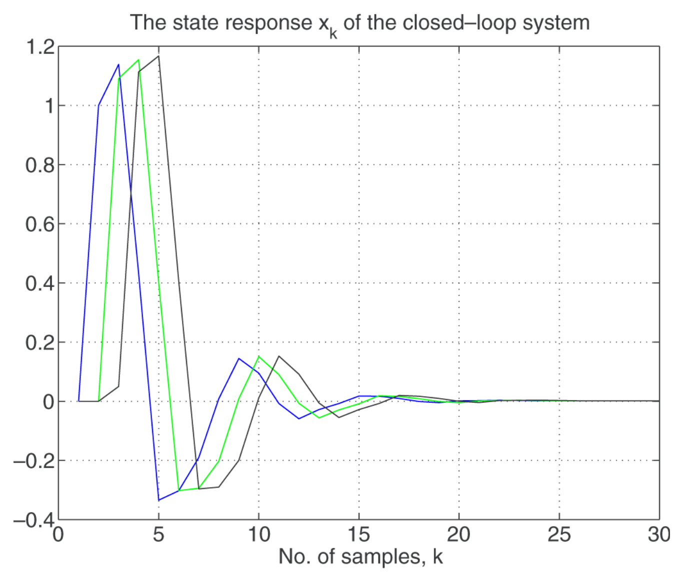

Fig. 2. H_∞ control with $\gamma_{\min} = 4.9549$.

Similar to the first case, the simulation result of the state responses given in Fig. 2 has confirmed that the controlled system is exponentially stable in the mean square.

Remark 5: We can observe from Figs. 1 and 2 that, when the packet losses are severer, the dynamical behavior of the NCS takes longer to converge to zero and, furthermore, the robustness of the closed-loop system is rather degraded, i.e., the minimum value $\gamma_{\min}$ in the second case is much larger than that in the first case.

V. Conclusion

In this paper, a novel robust H_∞ control problem has been considered for a class of networked systems with random communication packet losses. The random packet losses have been allowed to occur, simultaneously, in the communication channels from the sensor to the controller and from the controller to the actuator. In the presence of random packet losses, an observer-based feedback controller has been designed to robustly exponentially stabilize the networked system in the sense of mean square and also achieve the prescribed H_∞ disturbance-rejection-attenuation level. Both the stability-analysis and controller-synthesis problems have been investigated in detail. It has been shown that the controller-design problem under consideration is solvable if an LMI is feasible. Simulation results have demonstrated the feasibility of the addressed control scheme. One of our future research topics would be the study of NCSs with simultaneous packet dropout, network-induced delays, and quantized signal transmissions, where the latest delay-dependent techniques (e.g., [5] and [6]) can be employed.

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