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# Robust Packetized MPC for Networked Systems Subject to Packet Dropouts and Input Saturation With Quantized Feedback

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***Abstract*—This article develops a robust packetized predictive control framework to deal with the quantized-feedback control problem of networked systems subject to Markovian packet dropouts and input saturation. In the proposed framework, the Markov chain model of packet dropout is established from the link of the controller to the actuator. To deal with the quantized measurements, a robust packetized predictive control method is presented with a quantized-feedback law. The problem of unreliable transmission is addressed by proposing a packet dropout compensation strategy with a forgetting factor. An augmented Markovian jump system model is established to take the packet dropouts into account. The synthesis of packetized predictive control is then developed by minimizing a worst case cost function with respect to the model uncertainties. The recursive feasibility of the proposed controller design problem and the mean-square stability of the closed-loop systems are proved, respectively. The proposed packetized predictive control method is demonstrated by simulating a four-tank process system.**

***Index Terms*—Input saturation, networked systems, packetized predictive control, packet dropouts, quantized feedback.**

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## I. Introduction

In THE past few years, networking has been a major concern for system control and structure, attracting a lot of attention in distributed control for cooperative behaviors [1]–[4], that is, predictive control with deep learning [5], robust distributed predictive control with cost-effective approach [6], and hierarchical identification for sampled-data systems [7]. When it comes to cost and energy, model predictive control (MPC) is among the most important control tools for different process systems [8], [9]. The main advancement is that it can deal with system saturations and parameter uncertainties due to the predictive technique. Within this framework, the first basis is the system model, which is important for the MPC to give the future dynamics of a process. Then, a sequence of control actions is solved recursively at each sampling time. Finally, feedback correction is used to take the model errors/disturbances into account. Due to the complex working environment, model errors and disturbance are inevitable. Such complexities can result in instability of the considered systems [10], thus, which arise a mission to investigate robust MPC strategies with respect to parameter uncertainties and disturbances.

Recently, many researchers paid attention to the design and stability analysis of robust MPC [11]. For another, a novel robust MPC strategy was presented in [12] with a state-feedback law by minimizing the worst cost function for the systems subject to the model uncertainties. To deal with the unstructured uncertainty in the systems, a robust output-feedback MPC was also investigated in [13] with the application of an industrial continuous-stirred tank reactor (CSTR) problem. A periodic robust MPC control methodology was proposed in [14] for constrained nonlinear systems. A robust event-triggered MPC approach was developed with a guaranteed asymptotic bound and average sampling rate in [15]. However, the advancements in the above works are typically based on certainty and known information to design the controller, for example, a packet without dropouts. In practice, from the perspective of networked systems' framework with universities, a comprehensive structural framework called cyber–physical systems (CPSs) has become one of the hot topics for research and engineering [16]. In virtue of the rapid developments in computing science, hardware/software technology, and networking connections, these techniques can

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bring a lot of benefits to society, economy, and environment in different applications [17]. It is a truth that, under CPSs environment, the systems can be friendly connected with each other via the Internet and the transmission of the measurements and controls depend on the specific network structure [18]. However, since there is no prior information of receipt, the controller cannot discern the attainability of the previous packets. Therefore, for the synthesis of the controller design with cost optimization and packet dropouts, the stability and robustness for networked systems still remain challenging and open for the study.

It is not easy to design controllers for the networked control systems, that is, the measurements and the control actions are quantized and coded with digital networks [19]. From a control design perspective, many interesting challenges are associated with networked systems. For example, due to the inherent bit-rate limitations associated with digital networks, signals need to be quantized and coded prior to transmission. For the design of networked systems, one can often take the advantage of the fact that in contemporary communication networks, and data are sent in large timestamped packets [20]. Considering the control packet loss, a packetized MPC was developed in [21], in which the control packet loss was represented as a Bernoulli distribution. In [22], packetized MPC was investigated with dynamic scheduling constraints and bounded packet dropouts. The problems of stability analysis and controller synthesis of networked systems with quantizers were addressed in [23]. Generally, the quantizers for the data quantization of networked systems are either uniform or nonuniform. The uniform quantizer indicates that the control packets are quantized in an identical level [24]. The research interests are either from the controller to the actuator channel [25] or from the sensor to the controller side [26]. Besides, apart from data dropout in networked systems, due to physical limitations, actuator saturation becomes another challenge for networked systems.

In addition, input saturation becomes another difficult problem for networked systems [27]. The research on the controller design for systems subject to input saturation has become a new focus [28]. The disturbance rejection problem with the output control-feedback law for input saturated systems was developed in [29]. A robust quantized control scheme was proposed for uncertain systems with time delays and input saturation [30]. As far as we know, there are no results on packetized MPC for uncertain systems with both data loss and input saturation in the existing literature, which is more challenging in practice and motivates our current work.

The main feature of our work is to develop a robust packetized MPC framework to deal with the quantized-feedback control problem of systems subject to Markovian packet dropouts and input saturation. The main difficulties are: 1) the controller does not have information about whether previous packets are successfully transmitted to the plant and 2) the incorporation of the input saturation, model uncertainties, and quantized feedback into uniform representation simultaneously in robust MPC design. The contributions mainly include the following.

1) Presenting a compensation strategy with a forgetting factor to deal with the problem of packet loss.
2) Developing a packetized predictive control synthesis approach by minimizing an upper bound on the expected quadratic cost function with the infinite horizon.
3) Proving the recursive feasibility and the stability of the closed-loop system under the robust packetized MPC.

TABLE I
NOMENCLATURES

| Variables | Descriptions |
|---|---|
| $x(l,k)$ | future state at $k+l$, predicted at time instant $k$; |
| $u(l,k)$ | future input at $k+l$, predicted at time instant $k$; |
| $x(0,k)$ | state measurement of system at time instant $k$; |
| $sat(\cdot)$ | the standard saturation function; |
| $u^d(k)$ | control action of system, applied at $k$; |
| $u_s^d(k)$ | saturated input, i.e., $u_s^d(k) = sat(u^d(k))$; |
| $z(1,k)$ | augmented state $z(l,k) \triangleq \begin{bmatrix} x(l,k) \\ u_s^d(l,k-1) \end{bmatrix}$; |
| $\gamma(l,k)$ | a variable to indicate the packet dropouts at $k+l$; |
| $\alpha, \beta$ | the failure and the recovery probabilities; |
| $A^T$ | the transpose of matrix A; |
| $\mathbb{E}_z(a)$ | conditional expectation with respect to $a$ under $z$; |
| $V(l,k)$ | quadratic function $V(l,k) = z^T(l,k)Qz(l,k)$; |
| $P_{\gamma(l,k)}$ | positive definite matrices to penalty $x(l,k)$; |
| $G_{\gamma(l,k)}$ | positive definite matrices to penalty $u^d(l,k)$; |
| $\tau$ | the quantization density; |
| $\sigma$ | a constant $\sigma \triangleq \frac{1-\tau}{1+\tau}$; |
| $\Delta$ | quantization error defined as $\Delta \in [-\sigma, \sigma]$; |
| $\rho$ | an upper bound on cost function $J(k)$; |
| $h_\vartheta^T$ | the $\vartheta$-th row of the matrix $H$; |
| $\star$ | symmetric structure with $\begin{bmatrix} H & \star \\ N & R \end{bmatrix} = \begin{bmatrix} H & N^T \\ N & R \end{bmatrix}$; |
| $\triangleq$ | definition of a symbol. |

The outline of this article can be summarized as follows. Section II introduces the formulation of the considered problem. The design procedure of robust packetized MPC and the stability analysis are presented in Section III. Section IV proposes a four-tank process to illustrate the effectiveness. Finally, Section V draws the conclusion of this article. The notations are given in Table I.

## II. Preliminaries and Problem Formulation

This article proposes a networked control system framework to address the factors with Markovian packet dropouts, input saturation, and quantized feedback in the CPSs application. The framework is shown in Fig. 1, the real-time optimization layer provides the setpoints for the control layer. The objective is achieved by the process control layer. Due to the inherent bit-rate limitations associated with digital networks, signals need to be quantized and coded prior to transmission [21]. This work extends the recently developed MPC method to a kind of networked system with Markovian packet dropouts and saturation nonlinearity. A control method is developed in which packets of signal predictions are sent. The measurements are packetized before being transmitted from the sensor to the controller. This kind of design method under the network environment in MPC is known as packetized MPC.

The communication links exist in the transmission of both the physical plant to the controller and the controller to the actuator, which will lead to the following unavoidable issues: 1) quantized state-feedback link is built and the quantized-feedback-based MPC design is needed; 2) data

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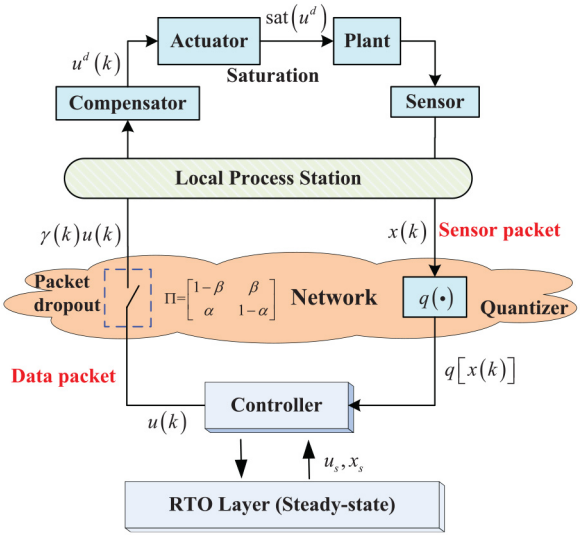


Fig. 1. Networked system's framework.

dropout between the controller and actuator is inevitable; and 3) due to the physical limitations or safety consideration, the control packet is saturated before being sent to the plant, which will degrade the control performance. These network-induced phenomenons can result in great challenges, that is, the compensation of the packet dropouts, the quantized-feedback controller design, the feasibility, and the stability.

Considering the following networked systems:

$$\begin{cases} x(k+1) = A(k)x(k) + B(k)\gamma(k)\text{sat}(u(k)) \\ 0 \le \Pr(\gamma(k+1) = 0 | \gamma(k) = 1) = \alpha \le 1 \\ 0 \le \Pr(\gamma(k+1) = 1 | \gamma(k) = 0) = \beta \le 1 \end{cases} \tag{1}$$

where $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$ are the state variable and the input variable, respectively, $A(k)$ and $B(k)$ represent the system matrices for the state and input, respectively, $q(\cdot)$ represents the logarithmic quantizer, and $\gamma(k)$ is used to indicate the situation of the data loss. $\Pr(a|b)$ is a conditional probability function.

Function $\text{sat}(\cdot)$ projects $\mathbb{R}^m$ to $\mathbb{R}^m$ is a standard saturation function, that is, $\sigma(u(k)) = [u_1(k), \ldots, u_m(k)]^T$ with $u_i(k) = \text{sign}(u_i(k)) \min\{1, |u_i(k)|\}$. A more general saturation level is transformed by applying the substitution $\hat{B} \Leftarrow BU$, $\hat{D} \Leftarrow DU$, $\hat{u} \Leftarrow U^{-1}u$, where $U = \text{diag}(u_{1,m}, \ldots, u_{m,m})$, and $u_{i,m}$ is the saturation level of the $i$-th control input.

Then, we have the general saturation level as follows:

$$\text{sat}(u_i(k)) = \begin{cases} -u_{i,m}, & u_i(k) < -u_{i,m} \\ u_i(k), & -u_{i,m} \le u_i(k) \le u_{i,m} \\ u_{i,m}, & u_i(k) > u_{i,m} \end{cases} \tag{2}$$

where $u_{i,m}$ denotes the upper bound of the input $u_i$. In practice, modeling errors are usually unavoidable [31]. The well-known polytopic uncertainties are considered in this article. We define $\lambda(k) \triangleq [\lambda_1(k), \ldots, \lambda_L(k)], 0 \le \lambda_i \le 1, \sum_{i=1}^{L} \lambda_i = 1$. The polytopic uncertain system matrices are given by $[A(k), B(k)] \in \Omega$, where $\Omega \triangleq Co\{[A^{(1)}, B^{(1)}], \ldots, [A^{(L)}, B^{(L)}]\}$, and $Co\{\cdot\}$ denotes the convex hull. Then, we have

$$[A(k), B(k)] = \sum_{i=1}^{L} \lambda_i \left[A^{(i)}, B^{(i)}\right]. \tag{3}$$

The logarithmic and time-variant quantizer is given by

$$\mathcal{X} = \{\pm x_j, j = 0, \pm 1, \pm 2, \ldots, \} \bigcup \{0\}. \tag{4}$$

A quantizer is logarithmic if the set of quantized levels are defined by

$$\mathcal{X} = \{\pm x_j, x_j = \tau^j x_0, j = 0, \pm 1, \pm 2, \ldots, \} \bigcup \{\pm x_0\} \bigcup \{0\}, 0 < \tau < 1, x_0 > 0. \tag{5}$$

We assume that each quantization level $x_j$ is modeled by a segment. Then, the quantizer can map the entire segments with the quantization level. The logarithmic quantizer is given as follows:

$$q(x) = \begin{cases} x_j, & \text{if } \frac{1}{1+\sigma} x_j < x < \frac{1}{1-\sigma} x_j \\ x > 0, & j = 0, \pm 1, \pm 2, \ldots \\ 0, & \text{if } x = 0 \\ -q(-x), & \text{if } x < 0 \end{cases} \tag{6}$$

where $x$ is the input of the quantizer, $x_j = \tau^j x_0$ are the outputs, $j = 0, \pm 1, \pm 2, \ldots$, $\tau$ is the quantization density of $q(\cdot)$ with $0 < \tau < 1$, and the constant $\sigma$ relates to $\tau$ by $\sigma \triangleq (1 - \tau/1 + \tau)$. Then, define the quantization error as follows:

$$e = q(x) - x = \Delta \cdot x. \tag{7}$$

Notably, quantization error is bounded by $\Delta \in [-\sigma, \sigma]$. Furthermore, $q(x)$ can be designed as follows:

$$q(x) = (1 + \Delta)x. \tag{8}$$

Then, a variable $\gamma(k)$ is introduced to define the situation of the data loss

$$\gamma(k) = \begin{cases} 1, \text{ if the packet is transmitted successfully} \\ 0, \text{ if the packet is lost.} \end{cases} \tag{9}$$

The packet dropout process is assumed to follow from a Markov chain with $\mathscr{W} = \{0, 1\}$. Then, the packet dropout situation is defined in (1) with a transition probability matrix

$$\Pi = \begin{bmatrix} 1-\beta & \beta \\ \alpha & 1-\alpha \end{bmatrix} \tag{10}$$

where $\alpha$ indicates the probability of packet loss and $\beta$ indicates the probability of recovery. To obtain our results, the following lemmas are introduced.

*Lemma 1 [32]:* Given a matrix $F$, let $\varphi(F) = \{x \in \mathbb{R}^n : |f_i^T x| \le 1, i = 1, \ldots, m\}$, where $f_i^T$ is the $i$th row of the matrix $F$. Let $P \in \mathbb{R}^{n \times n}$, $P > 0$, and $\gamma > 0$. An ellipsoid $\Omega(P, \gamma) = \{x \in \mathbb{R}^n : x^T P x \le \gamma\}$ is inside $\varphi(F)$ if and only if $f_i^T (\frac{P}{\gamma})^{-1} f_i \le 1, (i = 1, \ldots, m)$.

Define $\Xi$ as a set of $m * m$ diagonal matrix with elements 0 or 1. The number of elements in $\Xi$ is $2^m$. We assume the elements of $\Xi$ are labeled as $D_j$ with $j \in 1, \ldots, 2^m$. Denote $D_j^- \triangleq I - D_j$. Then, $D_j^-$ is also an element of $D_j$ if $D_j \in \Xi$.

*Lemma 2 [32]:* Given $F, H \in \mathbb{R}^{m \times n}$. Suppose that $h_i^T x \le 1$ for all $i = 1, \ldots, m$. Then, we have $\text{sat}(Fx) \in Co\{D_j F x +$

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$D_j^- Hx : j = 1, \ldots, 2^m\}$, where $h_i^T$ is the $i$th row of the matrix $H$.

Based on Lemmas 1 and 2, the input saturation $\text{sat}(Fx)$ will be cast into $\text{sat}(Fx) = \sum_{j=1}^{2^m} \eta_j (D_j Fx + D_j^- Hx)$.

*Lemma 3 [33]:* The mean-square closed-loop stability of (1) is guaranteed if $\mathbb{E}_{x(0)}\{\sum_{k=0}^{\infty} x^T(k)x(k)\} < \infty$ for any initial state $x(0)$.

*Remark 1:* The purpose of this article is to present a proper MPC approach to deal with the system saturations, parameter uncertainties, and packet dropouts for the networked environment. The model considered in our work incorporates with the randomly occurring packet dropouts and actuator saturations to address the CPSs environment with communication bandwidth limitations. Since there is no prior information of receipt, a key difficulty of this situation is that the controller does not have certain information about whether previous packets are successfully transmitted to the plant.

*Remark 2:* A robust packetized predictive control framework is proposed to address the quantized-feedback control problem for networked control systems. The synthesis of the controller design and the stability and robustness associated with CPSs are still challenging problems. The difficulties are the incorporation of the input saturation, uncertainties, and quantized feedback into uniform representation simultaneously in the robust MPC.

## III. Stochastic DMPC Design and Analysis of the Closed-Loop Stability

In this section, a state-feedback law $u(k) = F(k)q(x(k))$ is designed for the uncertain system with input saturations and packet dropouts for the networked environment. To address the problem of unreliable transmission, $u^d(k)$ is first introduced as follows:

$$u^d(k) = \begin{cases} u(k), & \gamma(k) = 1 \\ \delta u^d(k-1), & \gamma(k) = 0. \end{cases} \tag{11}$$

Based on (11), we obtain the packet compensation input for prediction as follows:

$$u^d(l,k) = \gamma(k)u(l,k) + (1-\gamma(k))\delta u^d(l,k-1). \tag{12}$$

where $u(l,k)$ denotes the input for time $k+l$, solved at time $k$; $u^d(l,k-1)$ denotes the input applied at time $k+l-1$.

The system model for prediction is described as follows:

$$x(l+1,k) = A(k)x(l,k) + B(k)\text{sat}\Big(u^d(l,k)\Big) \tag{13}$$

where $\delta \in [0,1]$ is a forgetting factor for tuning the control performance and $u^d(l,k)$ denotes the input for time $k+l$, predicted at time $k$.

Based on (8), the control input can be represented as $u(l,k) = F(k)q(x(l,k)) = \varrho F(k)x(l,k)$, where $\varrho \triangleq 1 + \Delta \in \big[1-\delta,\ 1+\delta\big]$. Furthermore, we obtain $\text{sat}[u^d(l,k)] = \text{sat}[\gamma(k)\varrho F(k)x(l,k)] + \text{sat}[(1-\gamma(k))\delta u^d(l,k-1)]$. By using Lemma 2, the input saturation is represented as $\text{sat}[\varrho F(k)x(l,k)] \triangleq \sum_{p=1}^{2^m} \eta_p \Psi(p,j)x(l,k)$, where $\Psi(p,j) \triangleq \gamma(k)\varrho D_p F + D_p^- H$. Let $u_s^d(l,k-1) \triangleq \text{sat}[u^d(l,k-1)]$, we obtain the following predictive model:

$$\begin{aligned} x(l+1,k) &= A(k)x(l,k) + B(k)\left\{\sum_{p=1}^{2^m} \eta_p \Psi(p,j)x(l,k) \right. \\ &\qquad \left. +(1-\gamma(k))\delta u_s^d(l,k-1)\right\} \\ &= \left\{A(k) + B(k)\sum_{p=1}^{2^m} \eta_p \Psi(p,j)\right\}x(l,k) \\ &\quad + B(k)(1-\gamma(k))\delta u_s^d(l,k-1). \end{aligned} \tag{14}$$

Furthermore, we obtain the compact form of the closed-loop system as follows:

$$\begin{aligned} x(l+1,k) &= \left[A(k) + B(k)\sum_{p=1}^{2^m} \eta_p \Psi(p,j)\right]x(l,k) \\ &\quad +(1-\gamma(k))\delta u_s^d(k-1) \\ &= \left[A(k) + B(k)\textstyle\sum_{p=1}^{2^m} \eta_p \Psi(p,j)\ (1-\gamma(k))\delta\right] \\ &\quad \left[\begin{matrix} x(l,k) \\ u_s^d(l,k-1)\end{matrix}\right]. \end{aligned} \tag{15}$$

Based on (12), the prediction of $u^d(l,k-1)$ becomes

$$\begin{aligned} u_s^d(l+1,k) &= \left[\gamma(k)\textstyle\sum_{p=1}^{2^m} \eta_p \Psi(p,j)\ (1-\gamma(k))\delta\right] \\ &\quad \times \left[\begin{matrix} x(l,k) \\ u_s^d(l,k-1)\end{matrix}\right]. \end{aligned} \tag{16}$$

By letting $z(l,k) \triangleq \left[\begin{matrix} x(l,k) \\ u_s^d(l,k-1)\end{matrix}\right]$, we obtain

$$z(l+1,k) = \Phi(k)z(l,k) \tag{17}$$

where

$$\Phi(k) = \begin{bmatrix} A(k) + B(k)\sum_{p=1}^{2^m} \eta_p \Psi(p,j) & (1-\gamma(k))\delta B(k) \\ \gamma(k)\sum_{p=1}^{2^m} \eta_p \Psi(p,j) & (1-\gamma(k))\delta I \end{bmatrix}.$$

The basic control problem of the MPC is to solve a sequence of control inputs $u(l,k), l = 0, \ldots, \infty$ to meet the control requirements. By using Lemma 2, the saturation constraint has been placed into the convex hull of a group of linear feedbacks in (17). Then, the objective here is to solve the following worst case optimization problem:

$$\min_{u(l,k), l=0,\ldots,\infty} \max_{[A(k),B(k)]\in\Omega} J(k), \ \text{s.t. (17)} \tag{18}$$

where $J(k) \triangleq \sum_{l=0}^{\infty} \mathbb{E}_{z(k)}\{\|z(l,k)\|_{\overline{Q}}^2 + \|u(l,k)\|_R^2\}$, and $\overline{Q} \triangleq \text{diag}\{Q,0\}$ with $Q \geq 0$ and $R > 0$ are two weighting matrices of augmented states and inputs, respectively. Rather than using the finite horizon MPC to "tune" the parameters for stability, it is preferable to adopt the infinite horizon approach to guarantee the nominal stability [12].

Since we have to solve infinite control inputs $u(l,k), l = 0, 1, \ldots, \infty$, it is noted that (18) is computationally intractable due to the infinite-time horizon for $J(k)$. Generally, an upper

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bound on $J(k)$ is introduced to relax (18). Then, a quadratic function is defined to derive the robust stability of the system

$$V(l,k) = z^T(l,k)\begin{bmatrix} P_{\gamma(l,k)} & 0 \\ 0 & G_{\gamma(l,k)} \end{bmatrix} z(l,k) \tag{19}$$

where $P_{\gamma(l,k)} \in \mathbb{R}^{n\times n}$ and $G_{\gamma(l,k)} \in \mathbb{R}^{n\times n}$ are two positive-definite matrices and $\gamma(l,k) \in \mathscr{W} = \{0,1\}$. Notably, the stability is ensured if following robust stability condition holds:

$$\begin{aligned} &\mathbb{E}_{z(k)}\{V(l+1,k) - V(l,k)\} \\ &\quad \le -\mathbb{E}_{z(k)}\left\{\|z(l,k)\|_{\overline{Q}}^2 + \|u(l,k)\|_R^2\right\}. \end{aligned} \tag{20}$$

If the (20) is summed with $l = 0$ to $l = \infty$, we obtain the optimization problem $\max_{[A(k),B(k)]} J(k) \le V(0,k)$. Condition $\lim_{l\to\infty}\mathbb{E}\{z(l,k)\} = 0$ is guaranteed if condition (20) is satisfied. Letting $V(0,k) \le \rho$, we obtain $J(k) \le \rho$. Thus, an upper bound is imposed for the robust performance objective $J(k)$. The objective of the packetized MPC is transformed to design $F(k)$ to minimize an upper bound on $V(0,k)$, that is

$$\min_{F(k)} \max_{[A(k),B(k)]\in\Omega} \rho, \text{ s.t. (17), (20) and } V(0,k) \le \rho. \tag{21}$$

Thus, the packetized MPC is given by minimizing $\rho$ subject to the augmented system dynamics (17), the robust stability condition (20), and the upper bound condition $V(0,k) \le \rho$. Then, the following theorem is given to ensure the satisfaction of the condition (20) in the sense of linear matrix inequality.

*Theorem 1:* Given $\tau$, and a forgetting factor $\delta$, (20) is satisfied if there are $\rho > 0$, positive-definite matrices $\overline{P}_0$, $\overline{G}_0$, $\overline{P}_1$, $\overline{G}_1$, $\overline{W}_0$, $\overline{T}_0$, $\overline{W}_1$, and $\overline{T}_1$, and matrices $Y$ and $Z$, guaranteeing the following conditions:

$$\begin{bmatrix} \begin{bmatrix} \overline{P}_1 & 0 \\ 0 & \overline{G}_1 \end{bmatrix} & \star \\ L_{12}^{(i,q,p)} & L_{22} \end{bmatrix} \ge 0$$
$$i = 1,\ldots,L, p = 1,\ldots,2^m, q = 1,2 \tag{22}$$

$$\begin{bmatrix} \begin{bmatrix} \overline{W}_1 & 0 \\ 0 & \overline{T}_1 \end{bmatrix} & \star \\ H_{12} & H_{22} \end{bmatrix} \ge 0 \tag{23}$$

$$\begin{bmatrix} \begin{bmatrix} \overline{P}_0 & 0 \\ 0 & \overline{G}_0 \end{bmatrix} & \overline{L}_{12}^{(i)} \\ \star & \overline{L}_{22} \end{bmatrix} \ge 0,\ i = 1,\ldots,L \tag{24}$$

$$\begin{bmatrix} \begin{bmatrix} \overline{W}_0 & 0 \\ 0 & \overline{T}_0 \end{bmatrix} & \overline{H}_{12} \\ \star & H_{22} \end{bmatrix} \ge 0 \tag{25}$$

where

$$H_{22} = \begin{bmatrix} \overline{P}_0 & 0 & 0 & 0 \\ 0 & \overline{P}_1 & 0 & 0 \\ 0 & 0 & \overline{G}_0 & 0 \\ 0 & 0 & 0 & \overline{G}_1 \end{bmatrix}$$

$$L_{22} = \begin{bmatrix} \overline{W}_1 & 0 & 0 & 0 \\ 0 & \overline{T}_1 & 0 & 0 \\ 0 & 0 & \rho\overline{Q}^{-1} & 0 \\ 0 & 0 & 0 & \rho R^{-1} \end{bmatrix}$$

$$\overline{L}_{22} = \begin{bmatrix} \overline{W}_0 & 0 & 0 & 0 \\ 0 & \overline{T}_0 & 0 & 0 \\ 0 & 0 & \rho\overline{Q}^{-1} & 0 \\ 0 & 0 & 0 & \rho R^{-1} \end{bmatrix}$$

$$L_{12}^{(i)} = \begin{bmatrix} A^{(i)}\overline{P}_1 + B^{(i)}[\varrho_q D_p Y + D_p^- Z] & 0 \\ \varrho_q D_p Y + D_p^- Z & 0 \\ \overline{P}_1 & 0 \\ \varrho_q D_p Y + D_p^- Z & 0 \end{bmatrix}$$

$$H_{12} = \begin{bmatrix} \alpha^{\frac{1}{2}}\overline{W}_1 & (1-\alpha)^{\frac{1}{2}}\overline{W}_1 & 0 & 0 \\ 0 & 0 & \alpha^{\frac{1}{2}}\overline{T}_1 & (1-\alpha)^{\frac{1}{2}}\overline{T}_1 \end{bmatrix}$$

$$\overline{L}_{12}^{(i)} = \begin{bmatrix} A^{(i)}\overline{P}_0 & \delta B^{(i)}\overline{G}_0 \\ 0 & \delta\overline{G}_0 \\ \overline{P}_0 & 0 \\ 0 & \delta\overline{G}_0 \end{bmatrix}$$

$$\overline{H}_{12} = \begin{bmatrix} (1-\beta)^{\frac{1}{2}}\overline{W}_0 & \beta^{\frac{1}{2}}\overline{W}_0 & 0 & 0 \\ 0 & 0 & (1-\beta)^{\frac{1}{2}}\overline{T}_0 & \beta^{\frac{1}{2}}\overline{T}_0 \end{bmatrix}.$$

*Proof:* This proof gives the conditions for the satisfaction of condition (20). By substituting (17) into (20), we have

$$\begin{aligned} &\mathbb{E}_{z(k)}\Big\{z^T(l,k)\Phi^T(l)\Theta_{\gamma(l+1,k)}\Phi(l)z(l,k) \\ &\quad - z^T(l,k)\Theta_{\gamma(l,k)}z(l,k) + \|z(l,k)\|_{\overline{Q}_i}^2 + \|u(l,k)\|_R^2\Big\} \le 0 \end{aligned} \tag{26}$$

where

$$\Phi(l) = \begin{bmatrix} A(k) + B(k)\sum_{p=1}^{2^m}\eta_p\Psi(p,j) & (1-\gamma(l,k))\delta B(k) \\ \gamma(l,k)\sum_{p=1}^{2^m}\eta_p\Psi(p,j) & (1-\gamma(l,k))I \end{bmatrix}$$

$$\Theta_{\gamma(l,k)} = \begin{bmatrix} P_{\gamma(l,k)} & 0 \\ 0 & G_{\gamma(l,k)} \end{bmatrix}$$

$$\Theta_{\gamma(l+1,k)} = \begin{bmatrix} P_{\gamma(l+1,k)|\gamma(l,k)} & 0 \\ 0 & G_{\gamma(l+1,k)|\gamma(l,k)} \end{bmatrix}.$$

Equation (26) is satisfied if

$$\begin{aligned} &\mathbb{E}_{z(l,k)}\left\{\Phi^T(l)\Theta_{\gamma(l+1,k)}\Phi(l)\right\} - \Theta_{\gamma(l,k)} + \mathrm{diag}\{Q,0\} \\ &\quad + \begin{bmatrix}\sum_{p=1}^{2^m}\eta_p\Psi(p,j)\ 0\end{bmatrix}^T R\begin{bmatrix}\sum_{p=1}^{2^m}\eta_p\Psi(p,j)\ 0\end{bmatrix} \le 0. \end{aligned} \tag{27}$$

Condition (27) is required to meet the robust stability. Two situations (i.e., $\gamma(l,k) = 1$ and $\gamma(l,k) = 0$) are proved to guarantee the satisfaction of condition (27). We will prove the theorem with the following two parts.

*Case 1:* $\gamma(l,k) = 1$ if the packet is received at time $k+l$. According to the transition probability matrix in (10), we have $\mathbb{E}_{\gamma(l,k)=1}\{\Theta_{\gamma(l+1,k)}\} = \alpha\mathrm{diag}\{P_0, G_0\} + (1-\alpha)\mathrm{diag}\{P_1, G_1\}$. Then, condition (27) is guaranteed if

$$\begin{aligned} &\Upsilon^T(k)\begin{bmatrix} W_1 & 0 \\ 0 & T_1 \end{bmatrix}\Upsilon(k) - \begin{bmatrix} P_1 & 0 \\ 0 & G_1 \end{bmatrix} + \begin{bmatrix} Q & 0 \\ 0 & 0 \end{bmatrix} \\ &\quad + \begin{bmatrix}\sum_{p=1}^{2^m}\eta_p\Psi(p,j) & 0\end{bmatrix}^T R\begin{bmatrix}\sum_{p=1}^{2^m}\eta_p\Psi(p,j) & 0\end{bmatrix} \le 0 \end{aligned} \tag{28}$$

$$\alpha\begin{bmatrix} P_0 & 0 \\ 0 & G_0 \end{bmatrix} + (1-\alpha)\begin{bmatrix} P_1 & 0 \\ 0 & G_1 \end{bmatrix} \le \begin{bmatrix} W_1 & 0 \\ 0 & T_1 \end{bmatrix} \tag{29}$$

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where

$$\Upsilon(k)=\begin{bmatrix} A(k)+B(k)\sum\limits_{p=1}^{2^m}\eta_p\Psi(p,j) & 0 \\ \sum_{p=1}^{2^m}\eta_p\Psi(p,j) & 0 \end{bmatrix}.$$

Let $\rho P_1^{-1}\triangleq\overline{P}_1$, $\rho G_1^{-1}\triangleq\overline{G}_1$, $\rho P_0^{-1}\triangleq\overline{P}_0$, $\rho G_0^{-1}\triangleq\overline{G}_0$, $\rho W_1^{-1}\triangleq\overline{W}_1$, and $\rho T_1^{-1}\triangleq\overline{T}_1$, pre- and post-multiply (28) with $\mathrm{diag}\{\rho^{\frac{1}{2}}P_1^{-1},\rho^{\frac{1}{2}}G_1^{-1}\}$, (29) holds if

$$\begin{aligned}&\begin{bmatrix} A^{(i)}\overline{P}_1+B^{(i)}\overline{\Psi}(p,j)\overline{P}_1 & 0 \\ \overline{\Psi}(p,j)\overline{P}_1 & 0\end{bmatrix}^T\begin{bmatrix}\overline{W}_1 & 0\\ 0 & \overline{T}_1\end{bmatrix}\\ &\quad\times\begin{bmatrix} A^{(i)}\overline{P}_1+B^{(i)}\overline{\Psi}(p,j)\overline{P}_1 & 0 \\ \overline{\Psi}(p,j)\overline{P}_1 & 0\end{bmatrix}-\begin{bmatrix}\overline{P}_1 & 0\\ 0 & \overline{G}_1\end{bmatrix}\\ &\quad+\begin{bmatrix}\overline{\Psi}(p,j)\overline{P}_1 & 0\end{bmatrix}^T\rho^{-1}R\begin{bmatrix}\overline{\Psi}(p,j)\overline{P}_1 & 0\end{bmatrix}\\ &\quad+\begin{bmatrix}\overline{P}_1 & 0\end{bmatrix}^T\rho^{-1}\overline{Q}\begin{bmatrix}\overline{P}_1 & 0\end{bmatrix}\le 0\end{aligned}\tag{30}$$

where $i=1,\ldots,L$, $p=1,\ldots,2^m$, $q=1,2$, and $\overline{\Psi}(p,j)\triangleq\gamma(k)\varrho_q D_p F+D_p^- H$. By letting $Y_1\triangleq F\overline{P}_1$, $Z_1\triangleq H\overline{P}_1$, $\varrho_1\triangleq 1-\delta$, and $\varrho_2\triangleq 1+\delta$, we obtain (22). Equation (29) is pre- and post-multiplied with $\mathrm{diag}\{W_1^{-1},T_1^{-1}\}$ and yields

$$\begin{aligned}\mathrm{diag}\Big\{&\overline{W}_1-\alpha\overline{W}_1\overline{P}_0^{-1}\overline{W}_1-(1-\alpha)\overline{W}_1\overline{P}_1^{-1}\overline{W}_1\\ &\overline{T}_1-\alpha\overline{T}_1\overline{G}_0^{-1}\overline{T}_1-(1-\alpha)\overline{T}_1\overline{G}_1^{-1}\overline{T}_1\Big\}\ge 0\end{aligned}\tag{31}$$

which can be rewritten as follows:

$$\begin{bmatrix}\overline{W}_1 & 0\\ 0 & \overline{T}_1\end{bmatrix}-H_{12}H_{22}^{-1}H_{12}^T\ge 0.\tag{32}$$

To this end, if (23) holds, condition (32) is satisfied.

*Case 2:* $\gamma(l,k)=0$ if the packet is lost at time $k+l$. With (10), we obtain

$$\Phi_0=\begin{bmatrix}\overline{A}_0(k) & \delta B(k)\\ 0 & I\end{bmatrix},\Theta_0=\begin{bmatrix}P_0 & 0\\ 0 & G_0\end{bmatrix}.$$

Furthermore, we obtain $\mathbb{E}_{z(l,k)=0}\{\Theta_{\gamma(l+1,k)}\}=\beta\mathrm{diag}\{P_1,G_1\}+(1-\beta)\mathrm{diag}\{P_0,G_0\}$. Equation (27) holds if

$$\begin{aligned}&\begin{bmatrix}A(k) & \delta B(k)\\ 0 & \delta I\end{bmatrix}^T\begin{bmatrix}W_0 & 0\\ 0 & T_0\end{bmatrix}\begin{bmatrix}\varrho A(k) & \delta B(k)\\ 0 & \delta I\end{bmatrix}\\ &\quad-\begin{bmatrix}P_0 & 0\\ 0 & G_0\end{bmatrix}+\begin{bmatrix}Q & 0\\ 0 & 0\end{bmatrix}+\begin{bmatrix}0 & \delta I\end{bmatrix}^T R\begin{bmatrix}0 & \delta I\end{bmatrix}\le 0\end{aligned}\tag{33}$$

$$\beta\begin{bmatrix}P_1 & 0\\ 0 & G_1\end{bmatrix}+(1-\beta)\begin{bmatrix}P_0 & 0\\ 0 & G_0\end{bmatrix}\le\begin{bmatrix}W_0 & 0\\ 0 & T_0\end{bmatrix}.\tag{34}$$

Let $\rho W_0^{-1}\triangleq\overline{W}_0$ and $\rho T_0^{-1}\triangleq\overline{T}_0$. Furthermore, (33) is pre- and post-multiplied with $\begin{bmatrix}\rho^{\frac{1}{2}}P_{i,0}^{-1} & 0\\ 0 & \rho^{\frac{1}{2}}G_0^{-1}\end{bmatrix}$ and obtain that (33) is guaranteed if (24) holds for $i=1,\ldots,L$ and $p=1,\ldots,2^m$. Multiplying both sides of (34) with $\mathrm{diag}\{W_0^{-1},T_0^{-1}\}$, we have $\mathrm{diag}\{\overline{W}_0-\beta\overline{W}_0\overline{P}_1^{-1}\overline{W}_0-(1-\alpha)\overline{W}_0\overline{P}_0^{-1}\overline{W}_0,\overline{T}_0-\alpha\overline{T}_0\overline{G}_1^{-1}\overline{T}_0-(1-\alpha)\overline{T}_0\overline{G}_0^{-1}\overline{T}_0\}\ge 0$, which can be rewritten as (25). This ends the proof. ∎

Condition $V(0,k)\le\rho$ is also need to be satisfied, we obtain

$$\begin{bmatrix}\rho & \star\\ z(0,k) & \begin{bmatrix}P_{\gamma(0,k)}^{-1} & 0\\ 0 & G_{\gamma(0,k)}^{-1}\end{bmatrix}\end{bmatrix}\ge 0.\tag{35}$$

Assuming that $\gamma(0,k)=1$, we have $P_{\gamma(0,k)}=P_1$ and $G_{\gamma(0,k)}=G_1$. Since $\rho P_1^{-1}\triangleq\overline{P}_1$ and $\rho G_1^{-1}\triangleq\overline{G}_1$, (35) is represented as follows:

$$\begin{bmatrix}1 & \star\\ z(0,k) & \begin{bmatrix}\overline{P}_1 & 0\\ 0 & \overline{G}_1\end{bmatrix}\end{bmatrix}\ge 0.\tag{36}$$

According to Lemma 1, the saturation constraints (2) must satisfy the condition $|h_\vartheta^T(k)x(k|k)|\le 1$. That is, we obtain $h_\vartheta^T(P_1/\rho)^{-1}h_\vartheta\le 1$, due to

$$\begin{aligned}h_\vartheta^T\left(\frac{P_1}{\rho}\right)^{-1}h_\vartheta&=h_\vartheta^T\rho_i(P_1)^{-1}h_\vartheta\\&=\left(\overline{P}_1h_\vartheta\right)^T\overline{P}_1^{-1}\overline{P}_1h_\vartheta\\&=\hbar_\vartheta^T\overline{P}_1^{-1}\hbar_\vartheta\end{aligned}\tag{37}$$

where $\hbar_\vartheta=\overline{P}_1h_\vartheta$, $\vartheta=1,\ldots,m$.

Then, the condition $|h_\vartheta^T(k)x(k|k)|\le 1$ is ensured by

$$\begin{bmatrix}1 & \hbar_\vartheta^T\\ \star & \overline{P}_1\end{bmatrix}\ge 0,\quad\vartheta=1,\ldots,m.\tag{38}$$

Then, the optimization problem of the proposed packetized MPC is summarized as follows:

$$\begin{aligned}\min_{\overline{P}_0,\overline{G}_1,\overline{P}_1,\overline{G}_0,\overline{W}_0,\overline{T}_1,\overline{W}_1,\overline{T}_1,Y,Z}\quad&\rho\\ \text{s.t.}\quad&(22)-(25),(36),(38).\end{aligned}\tag{39}$$

To this end, the control law is calculated by $F=Y\overline{P}_1^{-1}$. The following theorem will show that the proposed robust packetized MPC scheme is recursively feasible and can ensure the mean-square stability of the closed-loop system.

*Theorem 2:* For the quantized system (1) under the networked situations of packet dropouts and saturation, the optimization problem (39) is feasible for $k>k_0$ if it is feasible at $k=k_0$. Furthermore, with the robust MPC controller $u(k)=Y\overline{P}_1^{-1}x(k)$ obtained from (39), the closed-loop system of (1) is mean-square stable.

*Proof:* Since $z(0,k)$ in (36) depends on the real-time measurement $x(0,k)$, the optimization problem of packetized MPC controller is solved online to obtain a receding horizon state-feedback control law. We need to establish the recursive feasibility of the optimization problem. We will prove the theorem with two steps: 1) the feasibility of the optimization problem and 2) the stability of the closed-loop system.

1) *Recursive Feasibility:* The LMI in the problem that depends explicitly on the measured state $x(0,k)=x(k)$ of the system is (36). Thus, to prove the feasibility, we need to only prove that (36) is feasible for all future measured states $x(0,k+l)=x(k+l),l\ge 1$. At time $k=k_0$, the first packet is received, that is, $\gamma(0,k_0)=1$. It is assumed that (39) is feasible and the solutions are denoted as $\mathscr{F}^*(k_0)=\{\overline{P}_0^*,\overline{G}_1^*,\overline{P}_1^*,\overline{G}_0^*,\overline{W}_0^*,\overline{T}_1^*,\overline{W}_1^*,\overline{T}_1^*,Y^*,Z^*,\rho^*\}$. At time instant $k_0+1$, since (22)–(25), (38) do not depend on the measurement $z_i(k)$, and $\mathscr{F}^*(k_0)$ is also feasible for (22)–(25) and (38). In order to prove the feasibility of condition (36), we need to prove that the optimization problem (39) has feasible solutions for the new measurements $z(k+l),\ l=1,\ldots,\infty$. For the new measurement $z(k+1)$, we only need to prove that

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condition $V(1,k_0) \le \rho^*(k_0)$ is satisfied, which means that $\mathscr{F}^*(k_0)$ is a feasible solution for (36) at time instant $k_0+1$. From (20), we obtain $V(1,k_0) \le V(0,k_0) \le \rho^*(k_0)$. Condition $V(1,k_0) \le \rho^*(k_0)$ is satisfied since the measurement $z(k_0+1)$ is one of $z(1,k_0)$ under model uncertainty $[A(k),B(k)] \in \Omega$. It is proved that $\mathscr{F}^*(k_0)$ is a feasible solution for (39) at $k_0+1$. Furthermore, we need to prove that the optimization problem (36) has feasible solutions for the new measurements $z(k+l), l=2,\ldots,\infty$. Since $\gamma(0,k_0)=1$, two cases (i.e., $\gamma(1,k_0)=1$ and $\gamma(1,k_0)=0$) should be considered, respectively, at time instant $k_0+1$. Similarly, for $\gamma(1,k_0)=1$, we obtain $V(2,k_0) < \rho_i^*(k_0+1)$. For $\gamma(1,k_0)=0$, we have $V(2,k_0) \le V(1,k_0) \le V(0,k_0) < \rho^*(k_0)$. Since the measurement $z(k_0+2)$ is one of $z(2,k_0)$ under uncertainty $[A(k),B(k)] \in \Omega$, we have $V(k_0+2) \le \rho^*(k_0)$. To this end, $\mathscr{F}^*(k_0)$ is also a feasible solution for (39) at $k_0+2$. Similarly, it can be proved that the optimization problem (39) is also feasible for the subsequent sampling times.

2) *Stochastic Stability:* To show that stability, we need to prove that $\mathbb{E}_{z(k)}\{\sum_{k=0}^{\infty} x(k)^T x(k)\} < \infty$ holds for any initial $x(0)$. We still need to take the two situations (i.e., $\gamma(1,k_0)=1$ and $\gamma(1,k_0)=0$) into account. For $\gamma(0,k_0)=1$ and $\gamma(1,k_0)=1$, the optimal solutions of (39) at time $k_0$ and $k_0+1$ are denoted as $\mathscr{F}^*(k_0)$ and $\mathscr{F}^*(k_0+1)$, respectively. From the above analysis, we have $V(1,k_0) \le \rho^*(k_0)$. At time $k_0+1$, it is known that $\mathscr{F}^*(k_0+1)$ is the optimal solution and $\mathscr{F}^*(k_0)$ is only a feasible solution for (39), and we obtain $V(k_0+1) \le V(1,k_0)$ and $V(k_0+1) \le V(1,k_0) \le V(k_0) \le \rho^*(k_0)$. For the case $\gamma(0,k_0)=1$ and $\gamma(1,k_0)=0$, the packet is missed. Since we have $V(k_0+1) \le \rho^*(k_0)$, it is proved that $\sum_{l=0}^{\infty} \mathbb{E}_{z(k_0)}\{\|z(l,k_0)\|_{\bar{Q}}^2 + \|u(l,k_0)\|_{\bar{R}}^2\} \le \rho^*(k_0)$. Thus, $\mathbb{E}_{z(k_0)}\{\sum_{l=0}^{\infty} \|z(l,k_0)\|_{\bar{Q}}^2\} \le \infty$ is obtained. To this end, it is proved that the closed-loop system is stochastically stable. ■

The control objective is usually to steer the output to the origin or to an equilibrium state/output. The optimization problem (39) is usually used to control a system when the setpoint is constant. In the following, we will consider the setpoint tracking problems for the MPC algorithm. The system outputs are usually required to track reference trajectory $r$. The steady state $x_r$ and control input $u_r$ can be obtained by solving the following problem:

$$\begin{cases} x_r = A_r x_r + B_r u_r \\ r = C_r x_r \end{cases} \tag{40}$$

where $A_r$, $B_r$, and $C_r$ are the nominal system matrices of the system with known $\lambda_i$, $i=1,\ldots,L$. The cost function for the setpoint tracking problem can be defined as follows:

$$J(k) = \sum_{l=0}^{\infty} \mathbb{E}_{z(k)} \left\{ \|z(l,k) - z_r\|_{\bar{Q}}^2 + \|u(l,k) - u_r\|_{\bar{R}}^2 \right\} \tag{41}$$

where $z_r = \left[x_r^T \; u_r^T\right]^T$, $u_r$ denote the reference augmented states and inputs, respectively. In order to cast the tracking MPC problem into the standard form (39), a shifted state is defined as $\tilde{z}_k = z(k) - z_r$ and a shifted input is defined as $\tilde{u}(k) = u(k) - u_r$. The shifted state-space model can be represented as follows:

$$\begin{cases} \tilde{x}(l+1,k) = A(k)\tilde{x}(l,k) + B(k)\sigma(\tilde{u}(l,k)) \\ \tilde{y}(k) = C(k)\tilde{x}(k) \end{cases} \tag{42}$$

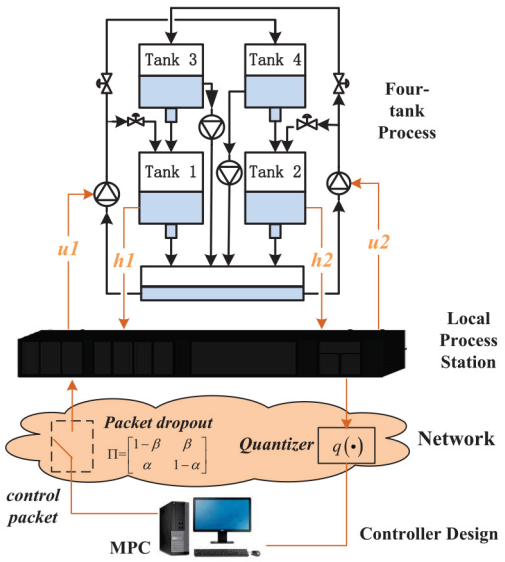


Fig. 2. Structure of the considered four-tank process.

with the initial state $\tilde{x}(0) = x(0) - x(0,r)$. Let $\tilde{Q} = C^T Q C$. We have the following cost function of setpoint tracking MPC problem:

$$\tilde{J}(k) = \sum_{l=0}^{\infty} \left( \|\tilde{x}(l,k)\|_{\tilde{Q}}^2 + \|\tilde{u}(l,k)\|_{\tilde{R}}^2 \right). \tag{43}$$

Then, the tracking MPC problem can be casted in to the standard LMI optimization problem (39) and the controller has the following form:

$$\tilde{u}(l,k) = F(k)(x(l,k) - x_r) + u_r. \tag{44}$$

The first control input $\tilde{u}(0,k)$ in the sequence is sent to the plant. The procedure is then repeated at the subsequent sampling times.

## IV. Application to Four-Tank Process

A four-tank process is derived to investigate to validate the control performance of the proposed method [34]. The schematic of this process is given in Fig. 2. For the application, the realistic process model is assumed to satisfy the polytopic uncertain and input saturation with $-30 \le u_{1,2} \le 30$. For the four-tank process subject to the randomly occurring packet dropouts and input saturation, the control objective is to track the given $h_1^r$ and $h_2^r$ with the control signals $u_1$ and $u_2$ designed by the proposed robust packetized MPC. Different from the general control situation, under the CPSs environment, the communication links exist in the transmission of control signals and measurements. A quantized state-feedback link is built and a quantized-feedback-based MPC design is needed. Besides, data dropout between the controller and the actuator is inevitable. Thus, the proposed robust packetized MPC is then tested in this four-tank process.

The influence of the packet dropout situation is tested with different $0 \le \alpha \le 1$, $0 \le \beta \le 1$. The solutions (i.e., $\mathscr{F}^*(k_0) = \{\overline{P}_0^*, \overline{G}_1^*, \overline{P}_1^*, \overline{G}_0^*, \overline{W}_0^*, \overline{T}_1^*, \overline{W}_1^*, \overline{T}_1^*, Y^*, Z^*, \rho^*\}$) of the optimization problem (39) depend on the tuning parameters $\alpha$ and $\beta$. It is also known that a larger $\beta$ and smaller $\alpha$

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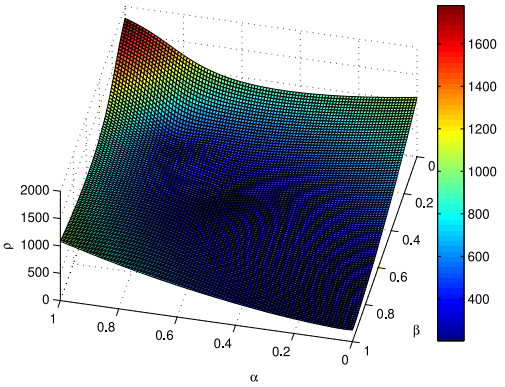


Fig. 3. Contour map of $\rho$ obtained by solving the optimization problem (39) with different $\alpha \in [0\ 1]$ and $\beta \in [0\ 1]$.

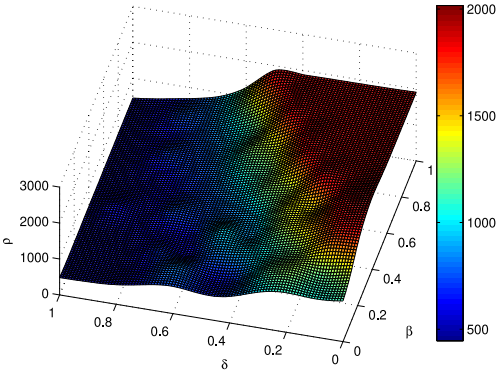


Fig. 4. Solutions of the optimization problem (39) with different $\alpha \in [0\ 1]$ and $\beta \in [0\ 1]$.

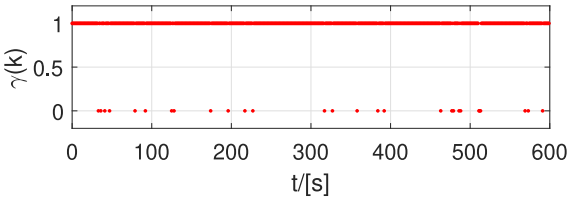


Fig. 5. Situations of packets under $\alpha = 0.05$ and $\beta = 0.95$.

mean that the network is more reliable. By repeatedly solving the optimization problem (39) with different $\alpha$ and $\beta$, we obtain different values of the decision variable $\rho$. Then, we obtain the upper bound of the cost function, that is, $J(k) \leq \rho$. In this end, $\rho$ can be used to reflect the control performance of the MPC strategy under different settings of parameters (i.e., $\alpha$, $\beta$). The 3-D plots of $\alpha$, $\beta$, and $\rho$ are shown in Fig. 3 by setting $\delta = 0$, $\beta \in [0\ 1]$, and $\alpha \in [0\ 1]$. The results indicate that, that the performance becomes worse if the packets are lost more frequently. Furthermore, we set $\beta \in [0\ 1]$ and $\delta \in [0\ 1]$ to test the control performances with respect to the forgetting factor and packet loss. The results show that better control performance will be achieved if a greater $\delta$ is chosen in this example (see Fig. 4). It is crucial to present a packet compensation strategy for the controller design. Next, we will test the performances of the proposed packetized MPC with packet compensation.

The discrete-time process model is given as follows [34]:

$$x(k+1) = A(k)x(k) + \gamma(k)B(k)u(k) \tag{45}$$

where $[A(k), B(k)] \in \Omega$, $\Omega \triangleq Co\{[A^{(1)}, B^{(1)}], [A^{(2)}, B^{(2)}]\}$,

$$A^{(1)} = \begin{bmatrix} 0.982 & 0.028 & 0 & 0.001 & 0 & 0 \\ 0 & 0.972 & 0.002 & 0 & 0 & 0 \\ 0 & 0 & 0.607 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.607 & 0 & 0 \\ 0 & 0 & 0.001 & 0 & 0.981 & 0.034 \\ 0 & 0 & 0 & 0.002 & 0 & 0.965 \end{bmatrix}$$

$$A^{(2)} = \begin{bmatrix} 0.990 & 0.028 & 0 & 0.001 & 0 & 0 \\ 0 & 0.980 & 0.002 & 0 & 0 & 0 \\ 0 & 0 & 0.607 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.607 & 0 & 0 \\ 0 & 0 & 0.001 & 0 & 0.990 & 0.034 \\ 0 & 0 & 0 & 0.002 & 0 & 0.970 \end{bmatrix}$$

$$B^{(1)} = \begin{bmatrix} 0 & 0 \\ 0 & 0.001 \\ 0 & 0.787 \\ 0.787 & 0 \\ 0 & 0 \\ 0.001 & 0 \end{bmatrix}, B^{(2)} = \begin{bmatrix} 0 & 0 \\ 0 & 0.001 \\ 0 & 0.791 \\ 0.791 & 0 \\ 0 & 0 \\ 0.001 & 0 \end{bmatrix}$$

$$y = \begin{bmatrix} h_1\ h_2 \end{bmatrix}^T, u^T = \begin{bmatrix} u_1\ u_2 \end{bmatrix}^T$$

$$x^T = \begin{bmatrix} h_1 & h_3 & v_2 & v_1 & h_2 & h_4 \end{bmatrix}^T.$$

The weighting matrices are $Q = 50{*}C_1^T C_1$ and $R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Tank level tracking and disturbance rejection problems are investigated in this case study.

1) Letting $\alpha = 0.05$ and $\beta = 0.95$, the packet dropout happens as in Fig. 5. The aim is to track the level of the Tanks 1 and 2 as follows:

$$h_1^r(k), h_2^r(k) = \begin{cases} 2, & 0 \leq k \leq 200 \\ 1, & 200 \leq k \leq 400 \\ 2.5, & 400 \leq k \leq 600. \end{cases} \tag{46}$$

2) The disturbances ($d_1(k)$ and $d_2(k)$) are, respectively, added to the states ($h_1(k)$ and $h_2(k)$) to show the efficiency of disturbance rejection. $d_1(k)$ and $d_2(k)$ are described as follows:

$$d_{1,2}(k) = \begin{cases} -0.2, & 20 \leq k \leq 22 \\ 0, & \text{others.} \end{cases} \tag{47}$$

The proposed packetized MPC algorithm is implemented for Monte Carlo simulations with forgetting factors $\delta = 0$ (no compensation), $\delta = 0.5$ (partial compensation), and $\delta = 1$ (full compensation) for SET 1. The root-mean-squared errors are shown in Fig. 6. The results show that better performance has been achieved if we apply the proposed packetized MPC method with the forgetting factor $\delta = 1$. The dynamical trajectories and the computed control actions are shown in Figs. 7–9. The results confirm that the proposed packetized MPC with compensation can achieve better control performances than the general MPC with partial or no compensation. The results also show that better control performance will be achieved if a greater $\delta$ is chosen in this example. The simulations are implemented in MATLAB on a PC, with a Dual-Core 2.50-GHz

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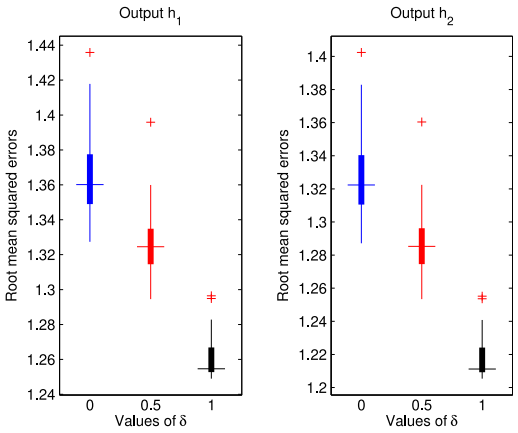


Fig. 6. Boxplots of the root mean-squared errors for four-tank process, obtained by solving (39) with $\delta = 0$ (blue), $\delta = 0.5$ (red), and $\delta = 1$ (black). "+" in the boxplot denote the outliers.

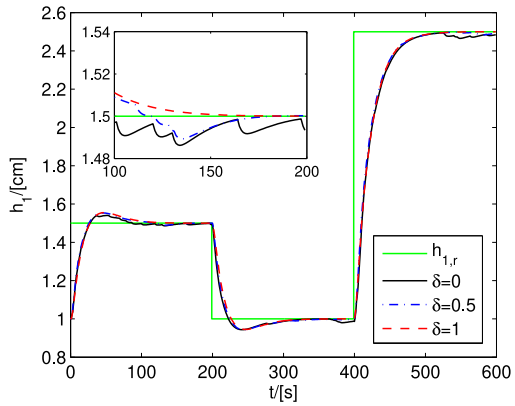


Fig. 7. Dynamic responses of $h_1$ under tracking problem with no compensation $\delta = 0$ (blue), partial compensation $\delta = 0.5$ (black), and full compensation $\delta = 1$ (red).

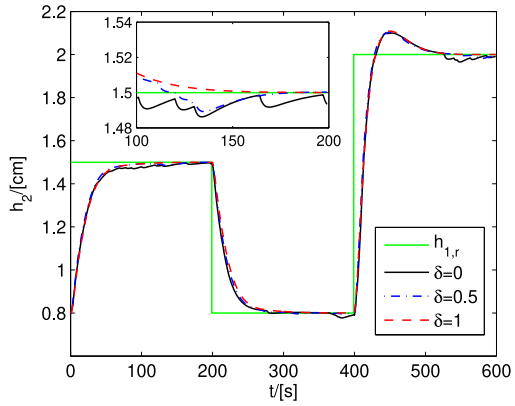


Fig. 8. Dynamic responses of $h_2$ under tracking problem with no compensation $\delta = 0$ (blue), partial compensation $\delta = 0.5$ (black), and full compensation $\delta = 1$ (red).

Intel i7 CPU and 16-GB RAM. The simulation time is about 0.6 s for each time instant.

For SET 2, under the disturbance rejection situation, the packetized MPC with no compensation $\delta = 0$ and full compensation $\delta = 1$, respectively, are used to test the performance. The system states are influenced by the disturbances during

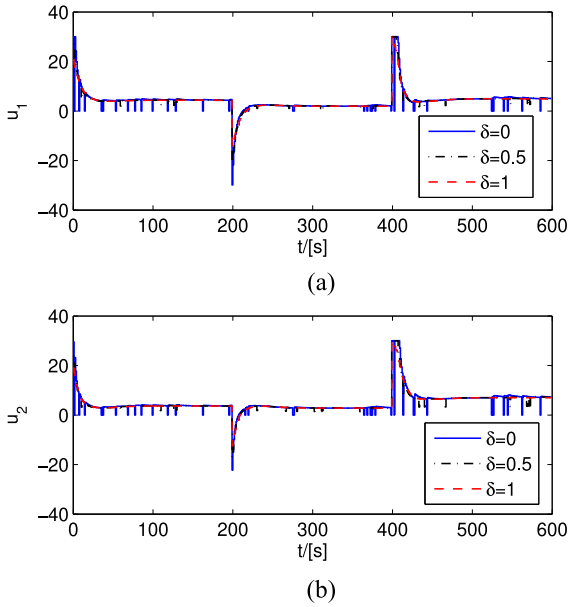


Fig. 9. Control inputs for tracking obtained by solving the optimization problem (39) with no compensation $\delta = 0$ (blue), partial compensation $\delta = 0.5$ (black), and full compensation $\delta = 1$ (red). (a) Computed control input $u_1$. (b) Computed control input $u_2$.

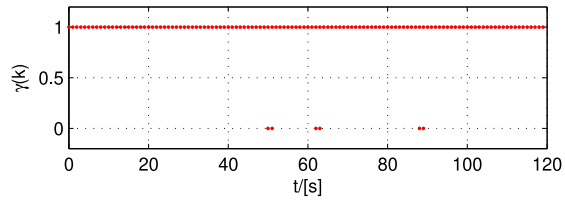


Fig. 10. Situations of packets with $\alpha = 0.05$ and $\beta = 0.95$ for disturbance rejection.

the time $k = 20$ to $k = 22$. The packet dropout situation is shown in Fig. 10. As shown in Fig. 11, the levels of the tanks are regulated to the expected outputs after the disturbances are removed. This indicates that the packetized MPC can achieve satisfactory disturbance rejection performance with the proposed compensation strategy.

## V. Conclusion

A robust packetized MPC framework is developed in this work to deal with the quantized-feedback control problem of networked systems subject to Markovian packet dropouts and input saturation. A packet dropout compensation with a forgetting factor is proposed to address the problem of unreliable transmission. The synthesis of packetized predictive control is developed by minimizing the worst cost function with respect to the model uncertainties and input situations. It is also shown that the proposed robust packetized predictive control scheme is recursively feasible and can achieve the mean-square stability of the closed-loop system. In the future, we can pay more attention to distributed packetized MPC of networked systems subject to packet dropouts and input saturation to reduce the computational complexity of the controller design.

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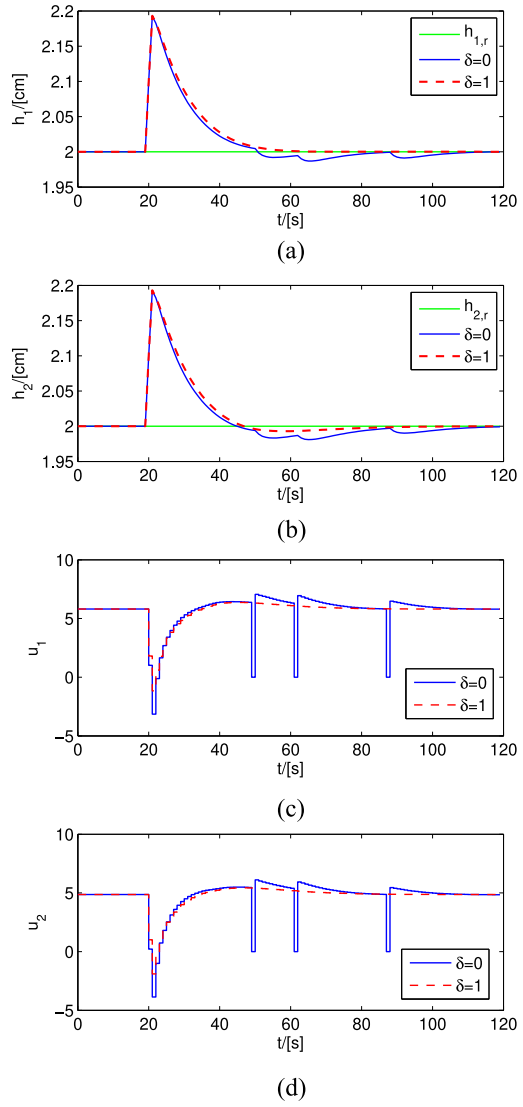


Fig. 11. Performances for the disturbance rejection with no compensation $\delta = 0$ and full compensation $\delta = 1$.

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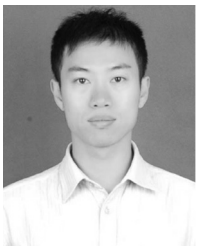

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