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Tracking Control Problem for Networked Stochastic System with Random Parameter Uncertainties Subject to Parallelly Occurring Deception Attacks

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Abstract: This paper is concerned with the tracking control problem for a class of discrete-time networked stochastic systems subject to parallelly occurring deception attacks (PODAs), where the random parameter uncertainties (RPUs) are simultaneously considered in the plant. To character the phenomenon of RPUs, a sequence taking values of 0 and 1 is employed, whose statistical characteristic is known in advance. Unfortunately, however, the deception attacks do not always occur in single form during the process of data transmission. The PODAs is thus proposed, whose description is successfully realized through two random variables behaving according to Bernoulli distribution. With aid of the aforementioned measurements, a desired output-feedback tracking controller is obtained. The aim of this paper is to develop an output-feedback controller for which the tracking error is exponentially ultimately bounded in the mean-square sense (EUBMS) as a result. The existence constraints on the eligible tracking controller are finally achieved in terms of linear matrix inequality. The reference output signal is tracked well by using the proposed tracking controller in a developed example with different inputs and disturbance, which thus fulfills the performance test.

Keywords: parameter uncertainties; networked stochastic systems; switching sequence; deception attacks; tracking control

1. Introduction

Tracking control, also known as model reference control [1,2], has been widely applied in real-time scenarios across industry, economics, bionics, and so forth [3]. Up to now, there have been numerous research results on tracking control, for instance, in the drive of induction motors and brushless DC motors, see e.g. [4], respectively. In addition to these areas, the achievement in [5] has already utilized tracking control for studying Quadrotor UAV (Unmanned Aerial Vehicle), a traditional model of unmanned aerial vehicle, along with the robust sliding mode control method. Besides, the reported achievement has implemented tracking control to adjust the position and attitude of the Quadrotor UAV which can been seen in [6]. Among others, it is valuable to highlight recent research achievements related to tracking control in fields such as robotics and spacecraft, see e.g. [7,8]. The dominating purpose of tracking control is to design controllers that enable the plant's output signal to closely follow the output of a predefined reference dynamics model. In recent years, there has been a growing body of research focusing on the stability analysis of tracking control, which can be learned from [9]. Additionally, the study in [10] investigated the tracking control problem for discrete-time nonlinear systems using standard neural network models, which differ from conventional discrete-time systems.

As is well known, for numerous real-world systems, equipments, controllers, sensors and front-end control areas cannot be located in the same place simultaneously due to the characteristics of the mechanical equipment and various potential constraints. To conquer this limitation, in practical engineering processes, these components are usually transmitted from one location to another. In modern industry, these components are often interconnected through networked media, such as electrical cables and optical fibers. Together, these components and networked media constitute the concept of networked control systems (NCSs). Due to their remarkable advantages such as low cost, lightweight, low energy consumption and simple installation, NCSs have received increasing attention in recent years, see e.g. [11]. Furthermore, the analysis of networked control systems has gradually emerged as a significantly researched field of interest in recent years. Among the results on NCSs, the research results in [12] addressed the stability problem of model-based networked control systems with time-varying transmission times. At the same time, stability analysis has been conducted for a class of typical networked control systems in [13]. Apart from this, focusing on the control problems, for example, the quantized control problem of NCSs under stochastic clock offsets has been addressed in [14].

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During the process of data transmission, parameter uncertainties are common phenomenon that will potentially have influence on the normal operation of our devices. The occurrence of parameter uncertainties is often unpredictable, that is to say they typically arise randomly. RPUs thus is proposed, which usually happen due to equipment maturing, environmental changes, parameter perturbations and some other factors. There have been quite a few achievements in analyzing the appearance of RPUs. Take an example, research in [15] has investigated the trajectory optimization problem of a drilling process considering parameter uncertainties, which is crucial for enhancing drilling efficiency and safety. Moreover, the adaptive stabilities for parabolic partial differential equation and ordinary differential equation systems with parameter uncertainties were discussed in [16], integrating with the actuator dynamics. More recently, research results on robust degradation state identification in the presence of parameter uncertainties have been carried out in [17]. Unfortunately, little progress has been made in solving the tracking control problem for discrete-time stochastic networked systems with RPUs. This paper aims to address this issue.

In real-time operational systems, cyber-attacks have emerged as one of the most significant threats to system security, primarily due to the inherent openness of communication channels [18]. Cyber-attacks are generally classified into denial-of-service (DoS) attacks, deception attacks and replay attacks. DoS attacks disrupt data communication mainly by consuming significant network resources [19]. Take the achievement in [20] as an example, the distributed set-membership filtering problem for discrete-time systems subjected to DoS attacks with fading measurements was carried out. Replay attacks degrade system performance by capturing the transmitted data and then replaying these previous data [21]. The analysis of replay attacks with countermeasure for state estimation of cyber-physical systems was investigated in [22]. By the way, the deception attacks hold back the transmission of system data with the method of replacing the normal transmission data with the malicious data [23]. Understanding and analyzing deception attacks is crucial, the reason lies in that they pose the severest threat to systems and often occur with high frequency. For instance, research in [24] has investigated the influence of hybrid cyber attacks on a class of multiarea power systems. Similarly, researchers have conducted deception attacks directly and proposed solutions to mitigate their impact on systems, see e.g. [25,26]. Last but not least, the issues addressed in these papers typically focus on single types of deception attacks, whereas in reality, deception attacks may occur parallelly and randomly. Therefore, this paper will study the problem of PODAs. Additionally, since deception attacks often occur in uncertain time, their randomness is typically represented by the introduction of variables that satisfy the Bernoulli distribution. The similar methods for dealing with randomly occurring events have been already applied in [27,28].

In this paper, we aim to address the tracking control problem for a class of stochastic discrete-time systems under the influence of RPUs and PODAs. The main contributions of this paper can be summarized as follows:

(1) The random occurrences of parameter uncertainties are simultaneously considered in the states of the networked system (i.e. RPUs), and such a comprehensive model is of thus more engineering practice.
(2) In the course of data communication, a novel concept of PODAs is put forward to describe the phenomenon of the random deception attacks occurring both in the plant and the reference dynamics.
(3) With help of the PODAs contaminated measurements including system measurement output and reference measurement output, an output-feedback controller is structured to efficaciously track the reference controlled output.
(4) The sufficient criteria to ensure the exponentially ultimate boundedness in mean-square sense of the tracking error are reached by resorting to the complicated and synthetical analysis.

The remainder of this paper is organized as follows. In Section 2, the tracking control problem for a class of discrete-time systems subject to the PODAs is formulated. The analysis of EUBMS of the tracking error and the design of the discussed output-feedback controller are conducted in Section 3. An illustrative example is provided in Section 4, and we conclude the paper in Section 5.

Notation: The notation used throughout the paper is fairly standard. I denotes the identity matrix of compatible dimension. For a matrix M, M^T and M^{-1} represent its transpose and inverse, respectively. The shorthand $\text{diag}\{M_1, M_2, \ldots, M_n\}$ denotes a diagonal matrix. $\mathbb{R}^m$ denotes the m-dimensional Euclidean space. The notation $X \geq Y$ (respectively, $X > Y$), where X and Y are symmetric matrices, means that $X - Y$ is positive semi-definite (respectively, positive definite). In symmetric block matrices, the symbol '$*$' is used as an ellipsis for terms induced by symmetry. $\|\cdot\|$ refers to the Euclidean norm in $\mathbb{R}^n$.

2. Problem Statement

Consider a class of discrete-time networked systems under the effect of RPUs as follows:

$$\begin{cases} x(k+1) = (A + \rho(k)\Delta)x(k) + u(k) + F\omega(k), \\ \quad y(k) = Cx(k), \\ \quad z(k) = Lx(k), \end{cases} \tag{1}$$

where $x(k) \in \mathbb{R}^m$ is the system state vector. $y(k) \in \mathbb{R}^n$ is the measurement output. $u(k) \in \mathbb{R}^q$ is the control input. $z(k) \in \mathbb{R}^p$ is the controlled output. $\omega(k) \in \mathbb{W} \triangleq \{\omega : \|\omega\| \leq \bar{\omega};\ \omega \in \mathbb{R}^{n_\omega}\}$ denotes the exogenous disturbance with $\bar{\omega} > 0$ being a known scalar. $\Delta \triangleq U\mathfrak{F}(k)W$ is the unknown time-varying matrix, which accounts for the parameter uncertainties with $\mathfrak{F}(k)\mathfrak{F}^T(k) \leq I$. $\rho(k)$ is the binary random switching sequence, which can describe the randomly occurring phenomenon by rule of the following:

$$\mathrm{Prob}\{\rho(k) = 1\} = \bar{\rho}, \quad \mathrm{Prob}\{\rho(k) = 0\} = 1 - \bar{\rho}, \tag{2}$$

where $\bar{\rho}$ is a given scalar. A, C, F, L, U and W are constant system matrices with appropriate dimensions.

Remark 1. *As is well known, parameter uncertainties is a ubiquitous phenomenon in networked systems due to various factors (e.g. component ageing, humiture variation of environment, perturbations and drifting of parameter, fluctuation of initial condition, and so forth). However, the emergence of parameter uncertainties is not changeless in network environment. In other words, the system parameters might be randomly perturbed by some network-induced reason (e.g. the unsteady network loads, network churn, etc.), which means the parameter uncertainties may appear in a random way. As such, a binary random switching sequences $\rho(k)$ is employed in the plant (1) to describe the RPUs.*

It is easy to know that, the networked systems may encounter deception attacks due to the open network environment during the process of data transmission. Unfortunately, deception attacks if mishandled will induce severe performance degradation of tracking control, and even system collapse. For this reason, the phenomenon of deception attacks is considered during the process of data transmission. Meanwhile, since both the output signals of the plant and the reference dynamics are all employed in the concerned state-feedback tracking controller, it is reasonable to consider the deception attacks in $y(k)$ and $y_r(k)$ simultaneously.

To character the phenomenon of PODAs, we introduce two Bernoulli random variables $\alpha(k)$ and $\beta(k)$ with mathematical expectation $\mathbb{E}\{\alpha(k)\} = \bar{\alpha}$ and $\mathbb{E}\{\beta(k)\} = \bar{\beta}$, where $\bar{\alpha}$ and $\bar{\beta}$ are given scalars. To characterize the occurrence of PODAs, we define the following random events:

$$\begin{cases} \text{Event 1: the deception attacks occur in (1)} \\ \text{Event 2: the deception attacks occur in (8)}\ . \end{cases}$$

Then the stochastic variable $\alpha(k)$ and $\beta(k)$ can be assigned by the following rules:

$$\alpha(k) = \begin{cases} 1, & \text{if Event 1 occurs} \\ 0, & \text{if Event 1 does not occur} \end{cases} \tag{3}$$

and

$$\beta(k) = \begin{cases} 1, & \text{if Event 2 occurs} \\ 0, & \text{if Event 2 does not occur.} \end{cases} \tag{4}$$

Assumption 1. *Throughout this paper, we assume that the stochastic Bernoulli variables $\alpha(k)$ and $\beta(k)$ are mutually independent.*

Subsequently, the transmission data of the plant and the reference dynamics subjected to PODAs can be formulated as follows:

$$\begin{cases} \bar{y}(k) = y(k) + \alpha(k)\varpi(k), \\ \bar{y}_r(k) = y_r(k) + \beta(k)\varpi_r(k), \end{cases} \tag{5}$$

where $\varpi(k)$ and $\varpi_r(k)$ are the malicious data replaced by deception attack [29]. The deception attacks signals can be modeled as follow:

$$\begin{cases} \varpi(k) = -y(k) + d(x(k)), \\ \varpi_r(k) = -y_r(k) + d(x(k)), \end{cases} \tag{6}$$

where $d(x(k)) \neq 0$ is an arbitrary bounded signal with a positive scalar $\bar{d}$ satisfying

$$d^T(x(k))d(x(k)) \leq \bar{d}. \tag{7}$$

The reference signals are governed by the following dynamics:

$$\begin{cases} x_r(k+1) = Gx_r(k) + r(k), \\ y_r(k) = Hx_r(k), \\ z_r(k) = Lx_r(k), \end{cases} \tag{8}$$

where $x_r(k) \in \mathbb{R}^m$ is reference state. $y_r(k) \in \mathbb{R}^n$ is the measurement output of the reference system. $z_r(k) \in \mathbb{R}^p$ is the controlled output of the reference system. $r(k)$ represents the reference input satisfying $r(k) \in \mathbb{R} \triangleq \{r : \|r\| \leq \bar{r}; \quad r \in \mathbb{R}^{n_r}\}$. G and H are appropriately dimensioned constant matrices.

The aim of the tracking control in this paper is to design an output-feedback controller such that the controlled output signal $z(k)$ in (1) can follow the trajectory of the controlled output signal $z_r(k)$ in (8). The block diagram of the proposed tracking control problem for the discrete-time networked system under the PODAs is shown in Figure 1.

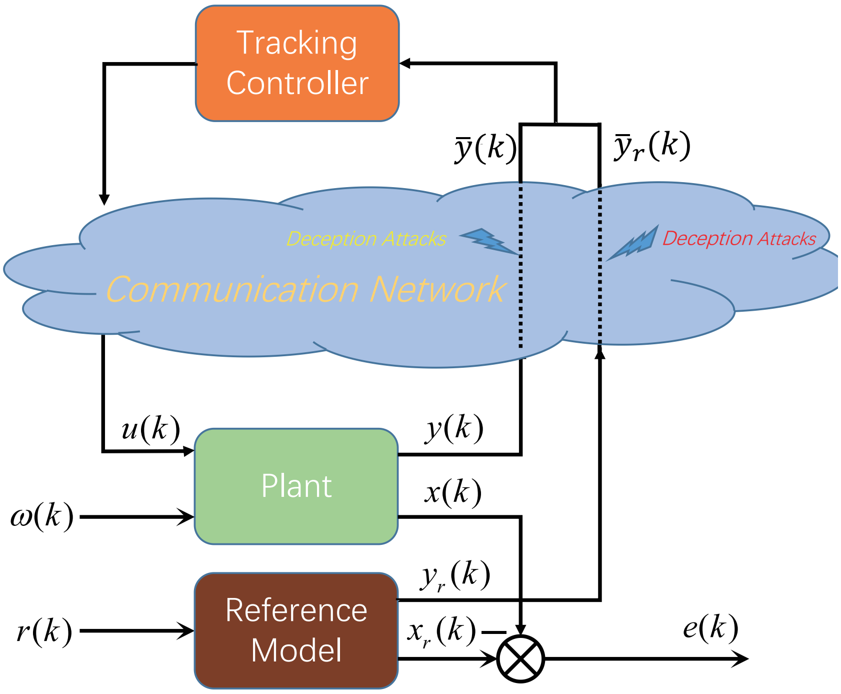

Figure 1. Block diagram of the tracking control under PODAs.

By taking advantage of the received measurement outputs (i.e. $y(k)$ and $y_r(k)$), the output-feedback tracking controller is structured as follows:

$$u(k) = K(\bar{y}(k) - \bar{y}_r(k)), \tag{9}$$

where K is the feedback tracking controller gain to be designed.

Remark 2. *On account of the high frequency of data transmission and network connections in NCSs, the occurrence of cyber-attacks is extraordinarily common. Among these previous research achievements, the discussed cyber attacks mainly covered the replay attacks [30] and the deception attacks. Two types of cyber-attacks mentioned earlier can halt the transmission of control signals and sensor data by blocking the communication channels [31]. The distinction lies in deception attacks, which directly hinder information transmission by substituting normal data with malicious data. The forms of the malicious signal may be various, and the condition here is only a nonlinear case. Because of this variety, it can greatly affect the operation of the controller. Under the action of some extreme malicious signal forms, it may eventually lead to no matter how the controller gain is designed and adjusted, the final tracking error will not reach convergence. There has been extensive research focusing on deception attacks, see e.g. [32,33]. However, the vast majority of former results only considered the deception attacks in isolation. Under this circumstance, the PODAs was introduced in this paper. Firstly, we proposed two random sequences following a Bernoulli distribution, which can partially indicate the randomness of the PODAs. Next, we designed an arbitrary bounded signal satisfying (7) to assist to model the deception attacks signals. Finally, we obtained the malicious signals $\bar{y}(k)$ and $\bar{y}_r(k)$ caused by PODAs, and formulated the output-feedback tracking controller considering the parallel deception attacks in the form of (9).*

By defining $\varepsilon(k) \triangleq x(k) - x_r(k)$ as the state tracking error, $e(k) \triangleq z(k) - z_r(k)$ as the controlled output tracking error [34], $\mathfrak{e}(k) \triangleq \begin{bmatrix}\varepsilon^T(k) & x_r^T(k)\end{bmatrix}^T$ and $o(k) \triangleq \begin{bmatrix}\omega^T(k) & r^T(k)\end{bmatrix}^T$, we can easily obtain the augmented tracking error closed-loop system under the interested feedback tracking controller subjected to PODAs from (1), (5), (8), and (9) as follows:

$$\begin{cases} \mathfrak{e}(k+1) = \mathcal{A}\mathfrak{e}(k) + \mathcal{B}d(x(k)) + \mathcal{F}o(k), \\ \quad e(k) = \mathcal{L}\mathfrak{e}(k), \end{cases} \tag{10}$$

where

$$\begin{aligned} &\mathcal{A} \triangleq \begin{bmatrix} \mathscr{A} & \mathscr{R} \\ 0 & G \end{bmatrix}, \quad \mathcal{B} \triangleq \begin{bmatrix} (\alpha(k) - \beta(k))K \\ 0 \end{bmatrix}, \\ &\mathcal{F} \triangleq \begin{bmatrix} F & -I \\ 0 & I \end{bmatrix}, \quad \mathcal{L} \triangleq \begin{bmatrix} L & 0 \end{bmatrix}, \\ &\mathscr{A} \triangleq A + \rho(k)\Delta + (1-\alpha(k))KC, \\ &\mathscr{R} \triangleq -G - (1-\beta(k))KH. \end{aligned}$$

Definition 1. *The dynamics of the tracking error $e(k)$ (i.e., the solution of system (10)) is EUBMS if there exist constants $\theta_i > 0 (i = 1, 2, 3)$ satisfying [35,36]*

$$\mathbb{E}\left\{\|e(k)\|^2\right\} \leq \theta_1^h \theta_2 + \theta_3, \tag{11}$$

where $0 \leq \theta_1 < 1$ denotes the decay rate, and θ_3 denotes the asymptotic upper bound of $\|e(k)\|^2$.

Our purpose in this paper is to design an output-feedback tracking controller in the form of (9) such that, for any RPUs and possible PODAs, the output tracking error dynamics $e(k)$ is EUBMS under the effect of the external noise $\omega(k)$ and the reference input $r(k)$.

3. Main Results

In this section, we will develop sufficient conditions to guarantee the EUBMS of the tracking error, and the controlled output signals of the plant can accurately follows the reference controlled output signals under the designed output-feedback controller. Before analysis implementation, we give out the following lemmas which will be used in the proofs of the main results.

Lemma 1. *(Schur Complement) Given constant matrices Σ_1, Σ_2, Σ_3 where $\Sigma_1 = \Sigma_1^T$ and $0 < \Sigma_2 = \Sigma_2^T$. Then $\Sigma_1 - \Sigma_3^T \Sigma_2^{-1} \Sigma_3 \geq 0$ if and only if*

$$\begin{bmatrix} \Sigma_1 & \Sigma_3^T \\ \Sigma_3 & \Sigma_2 \end{bmatrix} \geq 0 \quad \text{or} \quad \begin{bmatrix} \Sigma_2 & \Sigma_3 \\ \Sigma_3^T & \Sigma_1 \end{bmatrix} \geq 0. \tag{12}$$

Lemma 2. *For any real-valued vectors m, n, and matrix $Z > 0$ of compatible dimensions, the following holds [37];*

$$m^T Z n + n^T Z m \leqslant \vartheta m^T Z m + \frac{1}{\vartheta} n^T Z n \tag{13}$$

where $\vartheta > 0$ is a given constant.

Lemma 3. *[38] Let U, $\mathfrak{F}(k)$ and W be real matrices of appropriate dimensions with $\mathfrak{F}(k)$ satisfying $\mathfrak{F}^T(k)\mathfrak{F}(k) \leqslant I$. Then for any positive scalar ε,*

$$U\mathfrak{F}(k)W + W^T\mathfrak{F}^T(k)U^T < \varepsilon UU^T + \varepsilon^{-1}W^TW. \tag{14}$$

In the following theorem, an output-feedback tracking control problem subject to RPUs and PODAs will be dealt with for the systems (1) by using Lyapunov stability theory and matrix transform method. The sufficient condition in the form of matrix inequality will be established to solve the tracking control problem.

Theorem 1. *Let the scalar $\vartheta > 0$, and the tracking controller gain parameter K be given. The closed-loop system (10) with RPUs subjected to PODAs is EUBMS under the tracking controller (9) if there exists a positive-definite* *matrix P such that*

$$(1+\frac{1}{\vartheta})\mathcal{A}^T P\mathcal{A} - P + (1+\vartheta)\mathcal{B}^T P\mathcal{B} < 0. \tag{15}$$

Furthermore, if the condition (15) is feasible, the exponentially ultimate bound of the tracking error dynamics (10) is given as

$$\tilde{\delta} = \frac{\mu_0^T - 1}{\mu_0^{-T+1}(\mu_0 - 1)}\bar{\delta}, \tag{16}$$

where

$$\begin{aligned} b \triangleq& \lambda_{max}(\mathcal{B}^T P\mathcal{B}), \quad \bar{\delta} \triangleq b\bar{d} + \delta, \\ \delta \triangleq& (\bar{\omega} + \bar{r})\lambda_{max}(\mathcal{F}^T P\mathcal{F}). \end{aligned}$$

Proof. Now, we define the following Lyapunov function:

$$V(k) = \mathfrak{e}^T(k)P\mathfrak{e}(k). \tag{17}$$

Calculating the difference of $V(k)$ along the trajectory of the closed-loop system (10) and taking the mathematical expectation generate

$$\begin{aligned} \mathbb{E}\{\Delta V(k)\} =& \mathbb{E}\{V(k+1) - V(k)\} \\ =& \mathbb{E}\{\mathfrak{e}^T(k+1)P\mathfrak{e}(k+1) - \mathfrak{e}^T(k)P\mathfrak{e}(k)\} \\ =& \mathbb{E}\{\mathfrak{e}^T(k)\mathcal{A}^T P\mathcal{A}\mathfrak{e}(k) + \mathfrak{e}^T(k)\mathcal{A}^T P\mathcal{B}d(x(k)) \\ &+ d^T(x(k))\mathcal{B}^T P\mathcal{A}\mathfrak{e}(k) + d^T(x(k))\mathcal{B}^T P\mathcal{B}d(x(k)) \\ &- \mathfrak{e}^T(k)P\mathfrak{e}(k) + o^T(k)\mathcal{F}^T P\mathcal{F}o(k)\}. \end{aligned} \tag{18}$$

By considering the characteristic of $\omega(k)$ and $r(k)$ given in (1) and (8) respectively, it is easy to obtain

$$\mathbb{E}\{o^T(k)\mathcal{F}^T P\mathcal{F}o(k)\} \le \delta. \tag{19}$$

Then we conclude that

$$\begin{aligned} \mathbb{E}\{\Delta V(k)\} \le& \mathbb{E}\{\mathfrak{e}^T(k)\mathcal{A}^T P\mathcal{A}\mathfrak{e}(k) - \mathfrak{e}^T(k)P\mathfrak{e}(k) \\ &+ 2\mathfrak{e}^T(k)\mathcal{A}^T P\mathcal{B}d(x(k)) \\ &+ d^T(x(k))\mathcal{B}^T P\mathcal{B}d(x(k)) + \delta\} \\ =& \mathbb{E}\{\mathfrak{e}^T(k)\Pi_1\mathfrak{e}(k) + 2d^T(x(k))\Pi_2\mathfrak{e}(k) \\ &+ d^T(x(k))\Pi_3 d(x(k)) + \delta\}, \end{aligned} \tag{20}$$

where

$$\Pi_1 \triangleq \mathcal{A}^T P\mathcal{A} - P, \quad \Pi_2 \triangleq \mathcal{B}^T P\mathcal{A}, \quad \Pi_3 \triangleq \mathcal{B}^T P\mathcal{B}.$$

With aid of the Lemma 2, the expectation of the term $2d^T(x(k))\Pi_2\mathfrak{e}(k)$ can be reformulated as the following form:

$$\begin{aligned} \mathbb{E}\{2d^T(x(k))\Pi_2\mathfrak{e}(k)\} =& \mathbb{E}\{d^T(x(k))\mathcal{B}^T P\mathcal{A}\mathfrak{e}(k)\} \\ \le& \Bigg\{\vartheta d^T(x(k))\mathcal{B}^T P\mathcal{B}d(x(k)) \\ &+ \frac{1}{\vartheta}\mathfrak{e}^T(k)\mathcal{A}^T P\mathcal{A}\mathfrak{e}(k)\Bigg\}. \end{aligned} \tag{21}$$

It follows from (20) that

$$\mathbb{E}\{\Delta V(k)\} \leq \mathbb{E}\{\mathfrak{e}^T(k)\Phi_1\mathfrak{e}(k) + d^T(k)\Phi_2 d(k) + \delta\}, \tag{22}$$

where

$$\Phi_1 \triangleq \Pi_1 + \frac{1}{\vartheta}\mathcal{A}^T P\mathcal{A}, \quad \Phi_2 \triangleq \Pi_3 + \vartheta\mathcal{B}^T P\mathcal{B}.$$

Moreover, it can be obtained from (22) that

$$\begin{aligned}\mathbb{E}\{\Delta V(k)\} \leq & a\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} + b\mathbb{E}\{\|d(x(k))\|^2\} + \delta, \\ = & a\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} + \bar{\delta}.\end{aligned} \tag{23}$$

with $a = \lambda_{max}(\Phi_1)$.

On the other hand, it follows from the definition of the Lyapunov function in (17) that

$$\mathbb{E}\{V(k)\} \leq c\mathbb{E}\{\|\mathfrak{e}(k)\|^2\}, \tag{24}$$

with $c = \lambda_{max}(P)$. For any positive scalar $\mu > 1$, one has from (23) and (24) that

$$\begin{aligned}&\mu^{k+1}\mathbb{E}\{V(k+1)\} - \mu^k\mathbb{E}\{V(k)\} \\ &= \mu^{k+1}(\mathbb{E}\{V(k+1)\} - \mathbb{E}\{V(k)\})\mu^k(\mu-1)\mathbb{E}\{V(k)\} \\ &\leq \mu^{k+1}(a\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} + \bar{\delta} + \mu^k(\mu-1)c\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} \\ &= \mu^k(a\mu\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} + (\mu-1)c\mathbb{E}\{\|\mathfrak{e}(k)\|^2\}) + \mu^{k+1}\bar{\delta} \\ &= \mu^k\epsilon(\mu)\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} + \mu^k\bar{\delta},\end{aligned} \tag{25}$$

where $\epsilon(\mu) = a\mu + (\mu-1)c$. For any integer $T \geq 1$, summing up both sides of (25) from 0 to $T-1$ with respect to k results in

$$\begin{aligned}\mu^T\mathbb{E}\{V(T)\} - \mathbb{E}\{V(0)\} = & \epsilon(\mu)\sum_{k=0}^{T-1}\mu^k\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} \\ & + \frac{\mu(\mu^T-1)}{\mu-1}\bar{\delta}.\end{aligned} \tag{26}$$

It is obvious that $\epsilon(1) = a < 0$ and $\lim_{\mu\to+\infty}\epsilon(\mu) = +\infty$, one thus knows there exists a scalar $\mu_0 > 1$ such that $\epsilon(\mu_0) = 0$. So we can obtain from (26) that, for any integer $T \geq 1$,

$$\mu_0^T\mathbb{E}\{V(T)\} - \mathbb{E}\{V(0)\} \leq \frac{\mu_0(\mu_0^T-1)}{\mu_0-1}\bar{\delta}. \tag{27}$$

From (24), it is achieved that

$$\mu_0^T\mathbb{E}\{V(T)\} \leq c\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} + \frac{\mu_0(\mu_0^T-1)}{\mu_0-1}\bar{\delta}. \tag{28}$$

Subsequently, it gets

$$\mathbb{E}\{V(T)\} \leq c\mu_0^{-T}\mathbb{E}\{\|\mathfrak{e}(k)\|^2\} + \tilde{\delta}, \tag{29}$$

with

$$\tilde{\delta} \triangleq \frac{\mu_0^T-1}{\mu_0^{-T+1}(\mu_0-1)}\bar{\delta}.$$

By denoting $\theta_1 \triangleq \mu_0^{-1}, \theta_2 \triangleq c$, and $\theta_3 \triangleq \tilde{\delta}$, it follows from (11) that the tracking error dynamics (10) is EUBMS. This completes the proof. □

From Theorem 1, we have obtained the sufficient condition (1) to guarantee the system to be EUBMS in form of matrix inequality. Unfortunately however, the existence of the random variables (i.e. $\alpha(k)$, $\beta(k)$, and $\rho(k)$), the uncertain matrix Δ, and the nonlinear terms will inevitably bring great inconvenience to the acquisition of the gain parameter of the desired tracking controller. For this reason, the following theorem will be exploited to conquer such difficulties.

Theorem 2. *Let the scalars $\bar{\alpha}$, $\bar{\beta}$ and $\bar{\rho}$, and the positive scalars ε_1, ε_2 and ϑ be given. Then the tracking error $e(k)$ of the closed-loop system (10) with RPUs subjected to PODAs is EUBMS under the desired output-feedback tracking controller (9), if there exist a positive-definite matrix P and the matrix $\mathscr{K}$ such that*

$$\begin{cases} \bar{\Sigma}_1 < 0, \\ \bar{\Sigma}_2 < 0, \end{cases} \tag{30}$$

where

$$\begin{aligned}
&\bar{\Sigma}_1 \triangleq \begin{bmatrix} \bar{\Sigma}_1^{11} & * \\ \bar{\Sigma}_1^{21} & \bar{\Sigma}_1^{22} \end{bmatrix}, \quad \Sigma_2 \triangleq \begin{bmatrix} \Sigma_2^{11} & * \\ \Sigma_2^{21} & \Sigma_2^{22} \end{bmatrix}, \\
&\rho^* \triangleq \bar{\rho}(1-\bar{\rho}), \quad \alpha^* \triangleq \bar{\alpha}(1-\bar{\alpha}), \\
&\beta^* \triangleq \bar{\beta}(1-\bar{\beta}), \quad \gamma^* \triangleq (\bar{\alpha}-\bar{\beta})(1-\bar{\alpha}+\bar{\beta}), \\
&\bar{\Sigma}_1^{11} \triangleq \begin{bmatrix} -\varepsilon_2 I & * & * & * & * & * \\ \tilde{\Sigma}_1^{21} & -\varepsilon_1 I & * & * & * & * \\ 0 & \tilde{\Sigma}_1^{32} & -P & * & * & * \\ 0 & 0 & \bar{\Sigma}_{31} & -P & * & * \\ 0 & 0 & 0 & \Sigma_{32} & \tilde{\Sigma}_1^{55} & * \\ 0 & 0 & 0 & 0 & \Sigma_{42} & -P \end{bmatrix}, \\
&\tilde{\Sigma}_1^{21} \triangleq \sqrt{\rho^* + \frac{\rho^*}{\vartheta}} W, \quad \tilde{\Sigma}_1^{32} \triangleq \sqrt{\bar{\rho}^2 + \frac{\bar{\rho}^2}{\vartheta}} W, \\
&\tilde{\Sigma}_1^{55} \triangleq -P + \sqrt{\bar{\rho}^2 + \frac{\bar{\rho}^2}{\vartheta}} U^T U, \quad \Sigma_{42} \triangleq \sqrt{1 + \frac{1}{\vartheta}} H, \\
&\bar{\Sigma}_{31} \triangleq \sqrt{1 + \frac{1}{\vartheta}} (A + (1-\bar{\alpha})\mathscr{K} C), \\
&\Sigma_{32} \triangleq \sqrt{1 + \frac{1}{\vartheta}} \tilde{\Phi}_{15}, \quad \tilde{\Phi}_{15} \triangleq -G - (1-\bar{\beta})\mathscr{K} H, \\
&\bar{\Sigma}_1^{21} \triangleq \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & \tilde{\Sigma}_1^{15} \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \Sigma_{71} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \Sigma_{92} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \\
&\tilde{\Sigma}_{15} \triangleq -P + \sqrt{\rho^* + \frac{\rho^*}{\vartheta}} U^T U,
\end{aligned}$$

$$\begin{aligned}
&\Sigma_{71} \triangleq \sqrt{\alpha^* + \frac{\alpha^*}{\vartheta}} \mathscr{K} C, \quad \Sigma_{92} \triangleq \sqrt{\beta^* + \frac{\beta^*}{\vartheta}} \mathscr{K} H, \\
&\bar{\Sigma}_1^{22} \triangleq -I_6 \otimes P, \\
&\Sigma_2^{21} \triangleq \begin{bmatrix} \sqrt{1+\vartheta}\mathcal{B}_1 \\ \sqrt{\gamma^* + \vartheta\gamma^*}\mathcal{B}_2 \end{bmatrix}, \\
&\Sigma_2^{11} \triangleq -I, \quad \Sigma_2^{22} \triangleq -I_2 \otimes P, \\
&\mathcal{B}_1 \triangleq \begin{bmatrix} (\bar{\alpha}-\bar{\beta})\mathscr{K} \\ 0 \end{bmatrix}, \quad \mathcal{B}_2 \triangleq \begin{bmatrix} \mathscr{K} \\ 0 \end{bmatrix}.
\end{aligned}$$

Then the parameter gain of the investigated tracking controller (i.e. K) is achieved by $K = P^{-1}\mathscr{K}$.

Proof. By taking the stochastic closed-loop system (10) into consideration, the mathematical expectation of $\Delta V(k)$

in (22) can be reformulated as follows:

$$\begin{aligned}\mathbb{E}\{\Delta V(k)\} \leq &(1+\frac{1}{\vartheta})\mathbb{E}\{\mathfrak{e}^T(k)\mathcal{A}^T P\mathcal{A}\mathfrak{e}(k)\}\\ &+(1+\vartheta)\mathbb{E}\{d^T(x(k))\mathcal{B}^T P\mathcal{B}d(x(k))\}\\ &-\mathbb{E}\{\mathfrak{e}^T(k)P\mathfrak{e}(k)\}+\delta\\ =&(1+\frac{1}{\vartheta})\mathbb{E}\{\mathfrak{e}^T(k)(\mathcal{A}_1+\tilde{\rho}\mathcal{A}_2+\tilde{\alpha}\mathcal{A}_3+\tilde{\beta}\mathcal{A}_4)^T\\ &P(\mathcal{A}_1+\tilde{\rho}\mathcal{A}_2+\tilde{\alpha}\mathcal{A}_3+\tilde{\beta}\mathcal{A}_4)\mathfrak{e}(k)\}\\ &+(1+\vartheta)\mathbb{E}\{d^T(x(k))(\mathcal{B}_1+\tilde{\gamma}\mathcal{B}_2)^T P\\ &\quad(\mathcal{B}_1+\tilde{\gamma}\mathcal{B}_2)d(x(k))\}-\mathbb{E}\{\mathfrak{e}^T(k)P\mathfrak{e}(k)\}\\ &+\delta,\end{aligned} \tag{31}$$

where

$$\begin{aligned}&\mathcal{A}_1 \triangleq \begin{bmatrix}\tilde{\Phi}_{14} & \tilde{\Phi}_{15}\\ 0 & H\end{bmatrix}, \quad \mathcal{A}_2 \triangleq \begin{bmatrix}\Delta & 0\\ 0 & 0\end{bmatrix},\\ &\mathcal{A}_3 \triangleq \begin{bmatrix}\mathscr{K}C & 0\\ 0 & 0\end{bmatrix}, \quad \mathcal{A}_4 \triangleq \begin{bmatrix}0 & \mathscr{K}H\\ 0 & 0\end{bmatrix},\\ &\tilde{\Phi}_{14} \triangleq A+\bar{\rho}\Delta+(1-\bar{\alpha})\mathscr{K}C,\\ &\tilde{\rho} \triangleq \rho(k)-\bar{\rho}, \quad \tilde{\alpha} \triangleq \bar{\alpha}-\alpha(k),\\ &\tilde{\beta} \triangleq \beta(k)-\bar{\beta}, \quad \tilde{\gamma} \triangleq \alpha(k)-\bar{\alpha}-\beta(k)+\bar{\beta}.\end{aligned}$$

By noticing the characteristic of the mathematic expectation, the inequality (31) can be rewritten as follows:

$$\begin{aligned}\mathbb{E}\{\Delta V(k)\} \leq &(1+\frac{1}{\vartheta})\mathbb{E}\{\mathfrak{e}^T(k)(\mathcal{A}_1^T P\mathcal{A}_1+\rho^*\mathcal{A}_2^T P\mathcal{A}_2\\ &+\alpha^*\mathcal{A}_3^T P\mathcal{A}_3+\beta^*\mathcal{A}_4^T P\mathcal{A}_4)\mathfrak{e}(k)\}\\ &+(1+\vartheta)\mathbb{E}\{d^T(x(k))(\mathcal{B}_1^T P\mathcal{B}_1+\gamma^*\mathcal{B}_2^T P\mathcal{B}_2)\\ &d(x(k))\}+\delta.\end{aligned} \tag{32}$$

Now, with help of Schur Complement (Lemma 1), the condition obtained in Theorem 1 can be reformulated as follows:

$$\begin{cases}\Sigma_1 < 0\\ \Sigma_2 < 0,\end{cases} \tag{33}$$

where

$$\begin{aligned}&\Sigma_1 \triangleq \begin{bmatrix}\Sigma_1^{11} & *\\ \Sigma_1^{21} & \Sigma_1^{22}\end{bmatrix}, \quad \Sigma_2 \triangleq \begin{bmatrix}\Sigma_2^{11} & *\\ \Sigma_2^{21} & \Sigma_2^{22}\end{bmatrix},\\ &\Sigma_1^{11} \triangleq -P^{-1}, \quad \Sigma_1^{22} \triangleq -I_4\otimes P^{-1},\\ &\Sigma_1^{21} \triangleq \begin{bmatrix}\sqrt{1+\frac{1}{\vartheta}}\mathcal{A}_1\\ \sqrt{\rho^*+\frac{\rho^*}{\vartheta}}\mathcal{A}_2\\ \sqrt{\alpha^*+\frac{\alpha^*}{\vartheta}}\mathcal{A}_3\\ \sqrt{\beta^*+\frac{\beta^*}{\vartheta}}\mathcal{A}_4\end{bmatrix}.\end{aligned}$$

Pre- and post-multiplying the inequality (33) by $\mathrm{diag}_5\{P\}$ and its transpose, respectively, we obtain the Δ-dependent matrix inequality as follows:

$$\begin{cases}\tilde{\Sigma}_1 < 0,\\ \tilde{\Sigma}_2 < 0,\end{cases} \tag{34}$$

where $\tilde{\Sigma}_2$ is obtained by similarly pre- and post-multiplying the inequality (33) by $\mathrm{diag}\{I, P, P\}$ and its transpose. $\tilde{\Sigma}_1$

and $\tilde{\Sigma}_2$ has the same form of Σ_1 and Σ_2 with Σ_1^{11}, Σ_1^{22} and Σ_2^{22}, respectively, replaced by $\tilde{\Sigma}_1^{11}$, $\tilde{\Sigma}_1^{22}$ and $\tilde{\Sigma}_2^{22}$, where

$$\tilde{\Sigma}_1^{11} = -P, \quad \tilde{\Sigma}_1^{22} = -I_4 \otimes P, \quad \tilde{\Sigma}_2^{22} = -I_2 \otimes P.$$

By utilizing the methods before, we can ultimately eliminate the uncertain random binary sequences and obtain the matrix inequalities without random variables. Unfortunately, the occurrence of random parameter uncertainties can not be ignored either. On account of the influence brought by RPUs, the matrix inequality given above contain the unknown parameter $\mathfrak{F}(k)$. The next step of the theoretical analysis is to deal with the affect of the unknown item.

We rewrite the matrix inequality (33) with unknown parameter matrix Δ as follows:

$$\Sigma_1 = \begin{bmatrix} P_{11} & * \\ \Sigma_0 & P_{22} \end{bmatrix} < 0, \tag{35}$$

where

$$\begin{aligned}
&P_{11} \triangleq -I_2 \otimes P, \quad P_{22} \triangleq -I_8 \otimes P, \\
&\Sigma_0 \triangleq \begin{bmatrix} \Sigma_{31} & 0 & \Sigma_{51} & 0 & \Sigma_{71} & 0 & 0 & 0 \\ \Sigma_{32} & \Sigma_{42} & 0 & 0 & 0 & 0 & \Sigma_{92} & 0 \end{bmatrix}^T, \\
&\Sigma_{31} \triangleq \sqrt{1 + \frac{1}{\vartheta}}\tilde{\Phi}_{14}, \quad \Sigma_{51} \triangleq \sqrt{\rho^* + \frac{\rho^*}{\vartheta}}\Delta.
\end{aligned}$$

The matrices Σ_{31} and Σ_{51} can be split into:

$$\begin{aligned}
\Sigma_{31} &= \bar{\Sigma}_{31} + \Sigma_{31}', \\
\Sigma_{51} &= \sqrt{\rho^* + \frac{\rho^*}{\vartheta}}U\mathfrak{F}(k)W, \\
\Sigma_{31}' &= \sqrt{1 + \frac{1}{\vartheta}}\bar{\rho}U\mathfrak{F}(k)W.
\end{aligned}$$

For purpose of simplicity, we set

$$\begin{aligned}
T_1 &\triangleq \begin{bmatrix} 0\,0 & (\bar{\rho}^2 + \frac{\bar{\rho}^2}{\vartheta})^{(1/4)}U\ 0\,0\,0\,0\,0\,0\,0 \end{bmatrix}^T, \\
N_1 &\triangleq \begin{bmatrix} (\bar{\rho}^2 + \frac{\bar{\rho}^2}{\vartheta})^{(1/4)}W^T\ 0\,0\,0\,0\,0\,0\,0\,0\,0 \end{bmatrix}, \\
T_2 &\triangleq \begin{bmatrix} 0\,0\,0\,0\,(\rho^* + \frac{\rho^*}{\vartheta})^{(1/4)}U\ 0\,0\,0\,0\,0 \end{bmatrix}^T, \\
N_2 &\triangleq \begin{bmatrix} (\rho^* + \frac{\rho^*}{\vartheta})^{(1/4)}W^T\ 0\,0\,0\,0\,0\,0\,0\,0\,0 \end{bmatrix}, \\
\bar{\mathfrak{F}}(k) &\triangleq \mathrm{diag}_{10}\{\mathfrak{F}(k)\}.
\end{aligned}$$

Then the term $\mathcal{A}_1$ with parameter uncertainty given in (35) can be expressed by

$$\begin{aligned}
\Sigma_1 =& \Sigma_0 + T_1\bar{\mathfrak{F}}(k)N_1 + T_1^T\bar{\mathfrak{F}}^T(k)N_1^T + T_2\bar{\mathfrak{F}}(k)N_2 \\
&+ T_2^T\bar{\mathfrak{F}}^T(k)N_2^T,
\end{aligned} \tag{36}$$

where Σ_0 has the same form of Σ_1 with Σ_{31} and Σ_{51} replaced by $\bar{\Sigma}_{31}$ and zero.

Then by utilizing Lemma 3, the uncertain matrix $\mathfrak{F}(k)$ can be eliminated, and we thus arrive at:

$$\Sigma_1 < \Sigma_0 + \varepsilon_1 T_1 T_1^T + \varepsilon_1^{-1} N_1^T N_1 + \varepsilon_2 T_2 T_2^T + \varepsilon_2^{-1} N_2^T N_2. \tag{37}$$

Finally, with the aid of Lemma 1, it is easily to known that the condition (30) is solvable, which contains no uncertainties anymore. This completes the proof. The theoretical analysis of designed tracking controller is completed now. □

Remark 3. *In Theorem 1, in order to obtain the desired controller gain used to solve the problem of tracking* *control for networked stochastic system with RPUs subject to PODAs, we introduced the random variables $\alpha(k)$ and $\beta(k)$ to capture the randomness of PODAs, and $\rho(k)$ to represent the parameter uncertainties. However, due to the nondeterministic nature of these variables, the controller gain cannot be directly determined using Theorem 1. In this case, Theorem 2 is formulated to eliminate the random variables and transform the nonlinear terms in the matrix inequality into a linear form. For achieving the purpose of eliminating the random variables, the mathematical expectation should be incorporated into the calculation of the trajectory difference of the closed-loop system. The introduction of mathematical expectations into the proof process has been applied in papers related to random variables, as discussed in [39]. Apart from the random variables, to dispose the unknown time-varying matrix Δ, we introduced the Lemma 3 to address the problem. At the end of the Theorem 2, we transformed the nonlinear terms in the matrix inequality into a linear form, the linearizing approach is similar to the method used in [40]. Through these approaches, the desired controller gains can be obtained.*

4. Illustrative Example

In this section, a simulation example is developed to verify the advantages of the investigated output-feedback tracking controller subject to PODAs.

Firstly, the parameters of the system (1) are given as follows:

$$A=\begin{bmatrix}0.9580 & 0.9134\\ 0.1270 & 0.6324\end{bmatrix},\quad C=\begin{bmatrix}0.1 & 0\\ 0 & 0.2\end{bmatrix},$$
$$F=\begin{bmatrix}0.45\\ 0.92\end{bmatrix},\quad L=\begin{bmatrix}0.1 & 0.5\end{bmatrix},$$
$$U=\begin{bmatrix}0.06 & 0\\ 0 & 0.07\end{bmatrix},\quad W=\begin{bmatrix}0.3 & 0.1\\ 0.2 & 0.5\end{bmatrix}.$$

Additionally, the parameters of the reference system (8) are given as follows:

$$G=\begin{bmatrix}0.51 & 0\\ 0 & 0.62\end{bmatrix},\quad H=\begin{bmatrix}0.23 & 0.2\\ 0 & 0.53\end{bmatrix}.$$

Solving the constraint (30) (in Theorem 2) by using the MATLAB Control Toolbox and setting the scalars $\bar{\alpha}=0.5, \bar{\beta}=0.1, \bar{\rho}=0.35, \vartheta=0.5, \varepsilon_1=0.56$, and $\varepsilon_2=1.58$, one achieves the positive-definite matrix P and the matrix variable $\mathscr{K}$ as follows:

$$P=\begin{bmatrix}272.3443 & -13.4832\\ -9.3843 & 259.0718\end{bmatrix},$$
$$\mathscr{K}=\begin{bmatrix}52.2650 & -6.1507\\ -6.1507 & -44.3108\end{bmatrix}.$$

Furthermore, according to $K=P^{-1}\mathscr{K}$, the gain parameter of the desired output-feedback tracking controller can be successfully obtained as:

$$K=\begin{bmatrix}0.191075 & -0.031107\\ -0.016820 & -0.172163\end{bmatrix}.$$

Throughout all simulations, we set the initial values of (1) and (8) as $x(0)=[1.5-2.5]^T$ and $x_r(0)=[0.5-1.5]^T$, respectively. Setting the exogenous disturbance as $\omega(k)=0.1\sin(0.1k)$, and the reference input $r(k)$ as

$$r(k)=\begin{cases}0.1\sin(0.1k), & 0\le k\le 150\\ 0.05\sin(0.5k), & 200\le k\le 400\\ 0, & \text{otherwise.}\end{cases}$$

Let the nonlinear function $d(x(k))$ be $d(x(k))=5\cos(k)$. Obviously, the given $d(x(k))$ satisfies given assumption of $d(x(k))$ with the positive scalar $\bar{d}$.

Making use of all the parameters above, we give the trajectory of tracking error $e(k)$ under the desired output-feedback tracking controller in Figure 2. More specifically, the obtained tracking effects are shown in Figure 3. The figure shows the trajectory of the controlled output of plant (1) and reference dynamics (i.e. $z(k)$ and $z_r(k)$), respectively. Figure 3 thus consolidates our theoretical analysis of the suggested output-feedback tracking control method.

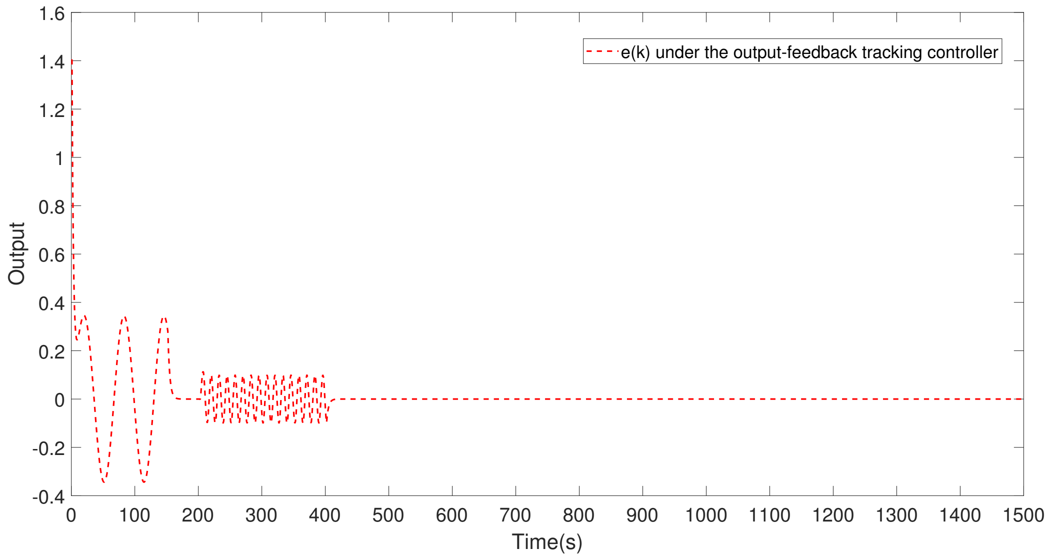

Figure 2. Trajectory of $e(k)$ under the output-feedback tracking controller.

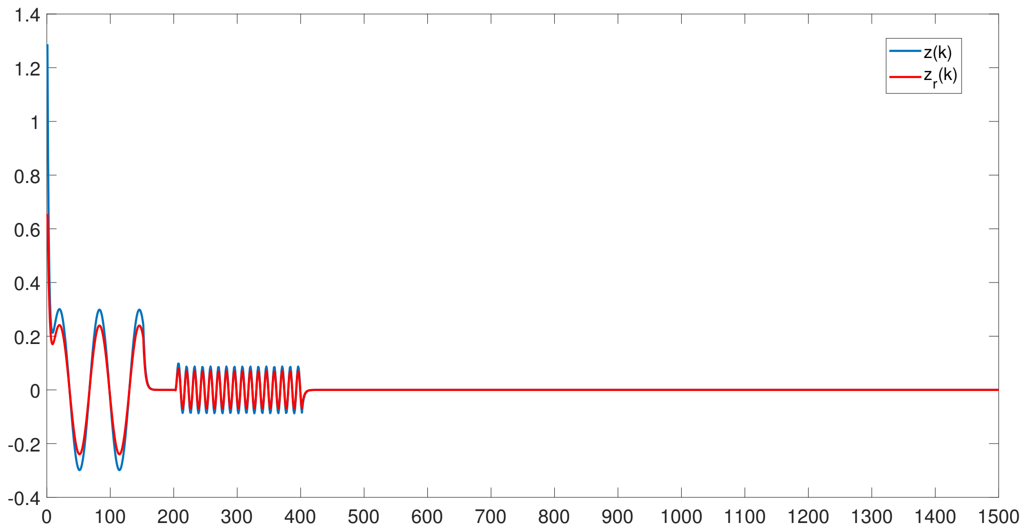

Figure 3. Trajectory of $z(k)$ and $z_r(k)$.

5. Conclusions

In this paper, a tracking control problem for a class of discrete-time networked stochastic systems with the RPUs and the bounded exogenous disturbance was investigated, along with a novel mechanism of deception attacks occurrence (i.e PODAs). To specifically express the phenomenon of RPUs, a time-varying unknown matrix was introduced along with the random binary sequence taking values of 0 and 1. Considering the randomness of the PODAs, two random variables satisfying Bernoulli distribution were utilized to model the presence of random PODAs. By using all of the aforementioned measurements, an output-feedback controller was implemented to obtain the achievements of tracking control. With aid of the introduction of the tracking error vector, an closed-loop tracking error augmented system was formulated to facilitate the analysis of the performance of the desired tracking controller. Such a similar approach has been taken in [41–43]. The analysis for EUBMS of the augmented tracking error system under the effect of designed tracking controller was conducted by using Lyapunov theory and the stochastic methodology. Then the feasible conditions of the desired controller were ultimately obtained, and the achieving approach of the output-feedback tracking gain was also discussed. Subsequently, one example involving differences of the external disturbances and the reference inputs was presented to validate our theoretical study.

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