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Passivity-based synchronization of stochastic switched complex dynamical networks with additive time-varying delays via impulsive control☆

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ABSTRACT

The issue of passivity-based synchronization for switched complex dynamical networks with additive time-varying delays, stochastic and reaction–diffusion effects is investigated. In this paper, stochastic, passivity theory and impulsive control are taken to investigate this problem. To reflect most of the dynamical behaviors of the system, both parameter uncertainties and stochastic disturbances are considered; stochastic disturbances are given in the form of a Brownian motion. By utilizing the Ito differential rule and matrix analysis techniques, we established a sufficient criterion such that, for all admissible parameter uncertainties and stochastic disturbances, the switched complex dynamical networks is robustly passive in the sense of expectation. By constructing a suitable Lyapunov–Krasovskii functional using Jensen's inequality, integral inequality technique and the passivity criterion of addressed complex dynamical networks is obtained. The derived criteria are expressed in terms of linear matrix inequalities that can be easily checked by using the standard numerical softwares. Illustrative example is presented to demonstrate the effectiveness and usefulness of the proposed results.

1. Introduction

In a complex network, each node represents a basic element with certain dynamical characteristics and information systems, while edges represent the relationship or connection of these basic elements. In general, the complexity of dynamical behaviors in such a network is governed by the following mechanism: the intrinsic dynamics at each node and diffusion due to the spatial coupling between nodes [1]. In particular, special attention has been focused on synchronization and control in large-scale complex networks composing of coupled chaotic dynamical systems. One of the reasons is that the complex networks have been extensively existed in many practical application, such as ecosystems, the Internet, scientific citation web, biological neural networks, large scale robotic system, etc., see e.g., [2–4]. The control and synchronization of complex dynamical networks have been extensively investigated in various fields of science and engineering due to its many potential practical applications. Synchronization, the most important collective behavior of complex dynamical networks (CDNs), has received much of the focus (see [5–8] and references there in). When modeling and implementing general complex dynamical networks, time-delay is often encountered in real applications due to the finite switching speed of amplifiers [9] which usually becomes a source of poor performance, oscillation, divergence and even instability [10]. In recent decades, considerable attention has been devoted to the time-varying delay systems due to their extensive applications in practical systems including circuit theory, chemical processing, bio engineering, complex dynamical networks, automatic control and so on [11–13]. In the implementation of complex dynamical networks, time-varying delay is unavoidably encountered due to the finite speed of signal transmission over the link and the network traffic congestions [14].

Generally speaking, the systems cannot achieve synchronization autonomously due to the existence of weak coupling or heterogeneity in the CDNs. Thus, it is necessary for us to inflict a control from external artificially. After researchers long-term exploration and unremitting efforts, many control strategies have been developed to drive complex networks to synchronize [15], such as adaptive control [16], intermittent control, impulsive control [17], pinning control, sampling data control [18], hybrid feedback control [19] and so on. Impulsive is a phenomenon that has been taken into consideration when modeling the complex networks. More

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recently, robust synchronization of complex dynamical networks has been seriously investigated by employing impulsive control strategies, several criteria for impulsive synchronization are established for uncertain complex dynamical networks (see [20,21] and references there in). On the other hand, known as part of a broader and a general theory of dissipativeness, Passivity theory plays an important role in stability analysis and control of dynamical systems [22]. The main point of passivity theory is that the passive properties of the system can keep the system internally stable. Passivity theory was first proposed in the circuit analysis [23] and since then it had found successful applications in diverse areas such as stability, signal processing, complexity, fuzzy control, chaos control, and synchronization [24–26]. Specifically, the passive system utilizes the product of input and output as the energy provision and embodies the energy attenuation character.

Switching signals can be divided into three categories: switching signals only depending on time, switching signals only depending on states and switching signals depending on time and states [27]. There are many practical switched systems in which switching signals depend on time. For example, in Yang and Zhu [28], the stability problem has been investigated for a class of the switched-capacitor power converter, in which the network mode switched from one to another according to time. In Wang et al. [29], the switching mechanism on time has been applied to the multi-agent systems. Clearly, the switching signal in the complex networks depending on time can be implemented easier than the switching signal depending on the state since it does not need to check the system states [30–32]. Stochastic disturbances and parameter uncertainties are to be considered in models. Because in real nervous system, synaptic transmission is a noisy process brought on by random fluctuation from the release of neurotransmitters, and the connection weights of the neuron depend on certain resistance and capacitance values that include uncertainties. Therefore, it is of practical importance to study the stochastic effects on the stability of complex dynamical networks (CDNs) with parameter uncertainties, some results related to this problem have been published in [33]. In addition, parameter uncertainties can be often encountered in real systems as well as complex dynamicals, due to the modeling inaccuracies and/or changes in the environment of the model. In the past few years, to solve the problem brought by parameter uncertainty, robustness analysis for different uncertain systems have been received considerable attention; [see, for example, [34]].

When we modeling real nervous systems, which are usually subjected to time delay, stochastic and impulsive perturbations that in turn affect dynamical behaviors of the systems. So it is important to consider the problems with influences of time delay, stochastic and impulsive perturbations [35]. Now, it has been well recognized that stochastic phenomenon is nearly inevitable owing to thermal noise in electronic devices in implementations of complex networks [36]. Some stochastic input could destabilize a complex network. Therefore, the synchronization problem for stochastic networks with time delay becomes more important from the practical point of view, see, for instance [37,38]. In signal transmission, the signal will become weak due to diffusion in signal transmission, so it is very important to consider that the activation varies in space as well as in time and the reaction–diffusion effects cannot be neglected in both biological and man-made networks [39,40]. As electrons transport in a nonuniform electromagnetic field, the diffusion phenomena could not be ignored. So it is significant to investigate the complex networks with diffusion terms, which can be described by partial differential equations.

Recently, many authors extensively studied the passivity synchronization problem for a class of CDNs with time delay [22,24,30]. In paper [26], the author studied the passivity analysis of impulsive coupled reaction–diffusion neural networks with and without time-varying delay. Regardless, to the best of our understanding, there are no reports on the passivity-based synchronization of uncertain stochastic switched complex dynamical networks with reaction–diffusion term. Pushed by the above talk and to fill this gap, we try to perform a passivity synchronization of conceded complex dynamical frameworks with additive time-delay. In this paper we plan to research the passivity-based synchronization of uncertain stochastic switched complex dynamical networks with reaction–diffusion term via impulsive control.

Motivated by the above, we investigate the passivity-based synchronization analysis for a class of stochastic switched complex dynamical networks with additive time-varying delays and parameter uncertainties.The problem of passivity analysis of a class of complex dynamical networks with additive time-varying delays in both the system state and output. In comparison to existing literature, the novelty of the present paper is threefold. A set of Lyapunov–Krasovskii functional method combined with the matrix analysis techniques is developed to obtain the sufficient conditions under which the system is globally robustly passive. By passivity theory, new delay-dependent synchronization criteria for uncertain stochastic switched complex dynamical networks with additive time-varying delays and reaction diffusion term is established in terms of LMIs, which allow simultaneous computation using numerically efficient LMI Control toolbox of two bounds that characterize the synchronization rate of the solution and can be easily determined. Finally, numerical examples and simulation are given to show the effectiveness and advantage of the present results.

Notation: $\mathbb{R}^n$ denotes the n dimensional Euclidean space and $\mathbb{R}^{m\times n}$ is the set of all $m\times n$ real matrices. The superscript "T" denotes matrix transposition and the notation $A\geq B$ (respectively, $A<B$) where A and B are symmetric matrices, means that $A-B$ is positive semidefinite (respectively, positive definite). $\|.\|$ denotes the Euclidean norm in $\mathbb{R}^n$. If S is a square matrix, denote by $\lambda_{max}(S)$ (respectively, $\lambda_{min}(S)$) means the largest(respectively, smallest) eigenvalue of S. $\mathcal{L}$ denote the diffusion operator, $\mathbb{E}$ denotes the expectation operator and $\Phi=\{x=(x_1,x_2,\ldots,x_m)\mid \varepsilon_1\leq x_\iota\leq\varepsilon_2, \varepsilon_1,\varepsilon_2\in R, \varepsilon_1\leq\varepsilon_2, \iota=1,2,\ldots,m\}$ is a compact set in space R^m with smooth boundary $\partial\Phi$ and its measure mes $\Phi>0$. The asterisk $*$ in a symmetric matrix is used to denote term that is induced by symmetry.

2. Problem formulation and preliminaries

Taking t, $x=(x_1,x_2,\ldots,x_m)^T$ as the time variable and space variable, respectively. We consider the following uncertain stochastic switched complex dynamical networks with additive time-varying delays and reaction–diffusion consisting of N identical nodes, in which each node is an n-dimensional dynamical models:

$$\begin{aligned}
du_z(x,t) &= [G_z\nabla^2 u_z(x,t)+(C_{\eta_k}+\triangle C_{\eta_k})u_z(x,t)\\
&\quad +(D_{1\eta_k}+\triangle D_{1\eta_k})f_{\eta_k}(u_z(x,t))+(D_{2\eta_k}+\triangle D_{2\eta_k})\\
&\quad \times f_{\eta_k}(u_z(x,t-\sigma_1(t)-\sigma_2(t)))\\
&\quad +a\sum_{j=1}^{N} q_{zj}^{\eta_k}\Upsilon_{\eta_k}u_j(x,t)+I_z(x,t)]dt+[(E_{\eta_k}+\triangle E_{\eta_k})u_z(x,t)\\
&\quad +(H_{\eta_k}+\triangle H_{\eta_k})u_z(x,t-\sigma_1(t)-\sigma_2(t))]dB_z(t), \quad t\neq t_\kappa\\
u_z(x,t_\kappa) &= J_\kappa u_z(x,t_\kappa^-), \qquad\qquad t=t_\kappa\\
u_z(x,t) &= \varphi_z(x,t), \quad (x,t)\in[-\sigma,0]\times\Phi, \quad z=1,2,\ldots,N,\\
u_z(x,t) &= 0, \qquad (x,t)\in[-\sigma,+\infty)\times\partial\Phi, \qquad (1)
\end{aligned}$$

where $u_z(x,t)\in\mathbb{R}^n$ represents the state of the z^{th} node of the system. a is the coupling strength; $\Upsilon_{\eta_k}=diag\{b_{a1\eta_k}, b_{a2\eta_k},\ldots,b_{an\eta_k}\}$ are constant diagonal inner-coupling matrices. $Q^{\eta_k}=(q_{zj}^{\eta_k})_{N\times N}$ is the outer-coupling matrix representing the topological