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Research Article

Robust L_2-L_∞ Filtering of Time-Delay Jump Systems with Respect to the Finite-Time Interval

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This paper studied the problem of stochastic finite-time boundedness and disturbance attenuation for a class of linear time-delayed systems with Markov jumping parameters. Sufficient conditions are provided to solve this problem. The L_2-L_∞ filters are, respectively, designed for time-delayed Markov jump linear systems with/without uncertain parameters such that the resulting filtering error dynamic system is stochastically finite-time bounded and has the finite-time interval disturbance attenuation γ for all admissible uncertainties, time delays, and unknown disturbances. By using stochastic Lyapunov-Krasovskii functional approach, it is shown that the filter designing problem is in terms of the solutions of a set of coupled linear matrix inequalities. Simulation examples are included to demonstrate the potential of the proposed results.

1. Introduction

Since the introduction of the framework of the class of Markov jump linear systems (MJLSs) by Krasovskii and Lidskii [1], we have seen increasing interest for this class of stochastic systems. It was used to model a variety of physical systems, which may experience abrupt changes in structures and parameters due to, for instance, sudden environment changes, subsystem switching, system noises, and failures occurring in components or interconnections and executor faults. For more information regarding the use of this class of systems, we refer the reader to Sworder and Rogers [2], Athans [3], Arrifano and Oliveira [4], and the references therein. It has been recognized that the time-delays and parameter uncertainties, which are inherent features of many physical processes, are very often the cause for poor performance of systems. In the past few years, considerable attention has been given to the robust control and filtering for linear uncertain time-delayed systems. A great amount of progress has been made on this general topic; see, for example, [5–8], and the references therein. As for MJLSs with time-delays and uncertain parameters, the results of stochastic stability, robust controllability, observability, filtering, and fault detection have been well investigated, and recent results can be found in [9–15].

It is now worth pointing out that the control performances mentioned above concern the desired behavior of control dynamics over an infinite-time interval and it always deals with the asymptotic property of system trajectories. But in some practical processes, a Lyapunov asymptotically stable system over an infinite-time interval does not mean that it has good transient characteristics, for instance, biochemistry reaction system, robot control system, and communication network system. Moreover, the main attention in these dynamics may be related to the behavior over a fixed finite-time interval. Therefore, we need to check the unacceptable values to see whether the system states remain within the prescribed bound in a fixed finite-time interval or not. To discuss this transient performance of control systems, Dorato [16] gave the concept of finite-time stability (or short-time stability [17, 18]) in the early 1960s. Then, some attempts on finite-time stability can be found in [19–24]. More recently, the concept of finite-time stability has been revisited in the light of recent results coming from linear matrix inequalities (LMIs) techniques, which relate the computationally appealing conditions guaranteeing finite-time stabilization [25, 26] of dynamic systems. Towards each case above, more details are related to linear control dynamics [27–29]. However, very few results in the literature consider the related control and filtering problems [30] of stochastic MJLSs in the finite-time interval. These motivate us to research this topic.

As we all know, since the Kalman filtering theory has been introduced in the early 1960s, the filtering problem has been extensively investigated, whose objective is to estimate the unavailable state variables (or a linear combination of the states) of a given system. During the past decades, the filtering technique regains increasing interest, and many filtering schemes have been developed. Among these filtering approaches, the L_2-L_∞ filtering problem [31, 32] has received less attention. But in practical engineering applications, the peak values of filtering error should be considered. And compared with H_∞ filtering, the stochastic noise disturbances are both assumed energy bounded in these two filtering techniques, but L_2-L_∞ filtering setting requires the L_2-L_∞ performance prescribed bounded from unknown noise disturbances to filtering error.

This paper is concerned with the robust L_2-L_∞ filtering problem for a class of continuous time-delay uncertain systems with Markov jumping parameters. We aim at designing a robust L_2-L_∞ filter such that, for all admissible uncertainties, time delays, and unknown disturbances, the filtering error dynamic system is stochastically finite-time bounded (FTB) and satisfies the given finite-time interval induced L_2-L_∞ norm of the operator from the unknown disturbance to the output error. By using stochastic Lyapunov-Krasovskii functional approach, we show that the filter designing problem can be dealt with by solving a set of coupled LMIs. In order to illustrate the proposed results, two simulation examples are given at last.

In the sequel, unless otherwise specified, matrices are assumed to have compatible dimensions. The notations used throughout this paper are quite standard. $\Re^n$ and $\Re^{n\times m}$ denote, respectively, the n dimensional Euclidean space and the set of all $n \times m$ real matrices. A^{T} and A^{-1} denote the matrix transpose and matrix inverse. $\mathrm{diag}\{A \quad B\}$ represents the block-diagonal matrix of A and B. If A is a symmetric matrix, denote by $\sigma_{\min}(A)$ and $\sigma_{\max}(A)$ its smallest and largest eigenvalues, respectively. $\sum_{i<j}^{N}$ denotes, for example, for $N = 3$,

$\sum_{i<j}^{N} a_{ij} \Leftrightarrow a_{12} + a_{13} + a_{23}$. $\mathbf{E}\{*\}$ stands for the mathematics statistical expectation of the stochastic process or vector and $\| * \|$ is the Euclidean vector norm. $L_2^n[0 \quad T]$ is the space of n dimensional square integrable function vector over $[0 \quad T]$. $P > 0$ stands for a positive-definite matrix. I is the unit matrix with appropriate dimensions. 0 is the zero matrix with appropriate dimensions. In symmetric block matrices, we use "$*$" as an ellipsis for the terms that are introduced by symmetry.

The paper is organized as follows. In Section 2, we derive the new definitions about stochastic finite-time filtering of MJLSs. In Section 3, we give the main results of L_2-L_∞ filtering problem of MJLSs and extend this to uncertain dynamic MJLSs in Section 4. In Section 5, we demonstrate two simulation examples to show the validity of the developed methods.

2. Problem Formulation

Given a probability space (Ω, F, P_r) where Ω is the sample space, F is the algebra of events and P_r is the probability measure defined on F. Let the random form process $\{r_t,\ t \geq 0\}$ be the continuous-time discrete-state Markov stochastic process taking values in a finite set $M = \{1, 2, \ldots, N\}$ with transition probability matrix $P_r = \{P_{ij}(t),\ i,\ j \in M\}$ given by

$$P_r = P_{ij}(t) = P\{r_{t+\Delta t} = j \mid r_t = i\} = \begin{cases} \pi_{ij}\Delta t + o(\Delta t), & i \neq j, \\ 1 + \pi_{ii}\Delta t + o(\Delta t), & i = j, \end{cases} \tag{2.1}$$

where $\Delta t > 0$ and $\lim_{\Delta t \to 0} o(\Delta t)/\Delta t \to 0$. $\pi_{ij} \geq 0$ is the transition probability rates from mode i at time t to mode j $(i \neq j)$ at time $t + \Delta t$, and $\sum_{j=1, j\neq i}^{N} \pi_{ij} = -\pi_{ii}$.

Consider the following time-delay dynamic MJLSs over the probability space (Ω, F, P_r):

$$\begin{gathered} \dot{x}(t) = A(r_t)x(t) + A_d(r_t)x(t-d) + B(r_t)w(t), \\ y(t) = C(r_t)x(t) + D(r_t)w(t), \\ z(t) = L(r_t)x(t), \\ x(t) = \lambda(t), r_t = \xi(t), t \in [t_0 - d \quad t_0], \end{gathered} \tag{2.2}$$

where $x(t) \in \Re^n$ is the state, $y(t) \in \Re^l$ is the measured output, $w(t) \in \Re^p$ is the unknown input, $z(t) \in \Re^q$ is the controlled output, $d > 0$ is the constant time-delay, $\sigma(t)$ is a vector-valued initial continuous function defined on the interval $[t_0 - d \quad t_0]$, and $\xi(t)$ is the initial mode. $A(r_t)$, $A_d(r_t)$, $B(r_t)$, $C(r_t)$, $D(r_t)$, and $L(r_t)$ are known mode-dependent constant matrices with appropriate dimensions, and r_t represents a continuous-time discrete state Markov stochastic process with values in the finite set $M = \{1, 2, \ldots, N\}$.

Remark 2.1. For convenience, when $r_t = i$, we denote $A(r_t)$, $A_d(r_t)$, $B(r_t)$, $C(r_t)$, $D(r_t)$, and $L(r_t)$ as A_i, A_{di}, B_i, C_i, D_i, and L_i. Notice that the time-delays in (2.2) are constant and only dependent of the system structure, and they are not dependent on the defined stochastic process. To simplify the study, we take the initial time $t_0 = 0$ and let the initial values

$\{\lambda(t)\}_{t\in[-d\quad 0]}$ and $\{\xi(t) = r_t\}_{t\in[-d\quad 0]}$ be fixed. At each mode, we assume that the time-delay MJLSs have the same dimension.

We now construct the following full-order linear filter for MJLSs (2.2) as

$$\begin{gathered}\dot{\widehat{x}}(t) = A_{fi}\widehat{x}(t) + A_{di}\widehat{x}(t-d) + B_{fi}y(t),\\ \widehat{z}(t) = C_{fi}\widehat{x}(t),\\ \widehat{x}(t) = \varphi(t), \qquad r_t = \xi(t), \quad t \in \left[-d \quad 0\right],\end{gathered} \tag{2.3}$$

where $\widehat{x}(t) \in \Re^n$ is the filter state, $\widehat{z}(t) \in \Re^q$ is the filter output, $\varphi(t)$ is a continuous vector-valued initial function, and the mode-dependent matrices A_{fi}, B_{fi}, and C_{fi} are unknown filter parameters to be designed for each value $i \in M$.

Define $e(t) = x(t) - \widehat{x}(t)$ and $r(t) = z(t) - \widehat{z}(t)$, then we can get the following filtering error system:

$$\begin{gathered}\dot{e}(t) = \left(A_i - B_{fi}C_i\right)x(t) - A_{fi}\widehat{x}(t) + A_{di}[x(t-d) - \widehat{x}(t-d)] + \left(B_i - B_{fi}D_i\right)d(t),\\ r(t) = L_i x(t) - C_{fi}\widehat{x}(t).\end{gathered} \tag{2.4}$$

Let $\overline{x}^T(t) = [x^T(t) \quad e^T(t)]$, the filtering error system (2.4) can be rewritten as

$$\begin{gathered}\dot{\overline{x}}(t) = \overline{A}_i\overline{x}(t) + \overline{A}_{di}\overline{x}(t-d) + \overline{B}_i w(t),\\ r(t) = \overline{C}_i\overline{x}(t),\\ \overline{x}^T(t) = \left[\lambda(t) \ \ \lambda(t) - \varphi(t)\right], \qquad r_t = \xi(t), \quad t \in [-d \quad 0],\end{gathered} \tag{2.5}$$

where

$$\begin{gathered}\overline{A}_i = \begin{bmatrix} A_i & 0 \\ A_i - A_{fi} - B_{fi}C_i & A_{fi}\end{bmatrix}, \qquad \overline{A}_{di} = \begin{bmatrix} A_{di} & 0 \\ 0 & A_{di}\end{bmatrix},\\ \overline{B}_i = \begin{bmatrix} B_i \\ B_i - B_{fi}D_i\end{bmatrix}, \qquad \overline{C}_i = \left[L_i - C_{fi} \ \ C_{fi}\right].\end{gathered} \tag{2.6}$$

The objective of this paper consists of designing the finite-time filter of time-delay MJLSs in (2.1) and obtaining an estimate $\widehat{z}(t)$ of the signal $z(t)$ such that the defined guaranteed L_2-L_∞ performance criteria are minimized. For some given initial conditions [24–27], the general idea of finite-time filtering can be formalized through the following definitions over a finite-time interval.

Assumption 1. *The external disturbance $w(t)$ is time-varying and satisfies*

$$\int_0^T w^T(t)w(t)dt \le W, \quad W \ge 0. \tag{2.7}$$

Definition 2.2. For a given time-constant $T > 0$, the filtering error MJLSs system (2.5) with $w(t) = 0$ is stochastically finite-time stable (FTS) if there exist positive matrix $R_i \in \Re^{2n\times 2n} > 0$ and scalars $c_1 > 0$ and $c_2 > 0$, such that

$$\mathbf{E}\left\{\overline{x}^T(t_1)R_i\overline{x}(t_1)\right\} \leq c_1 \Longrightarrow \mathbf{E}\left\{\overline{x}^T(t_2)R_i\overline{x}(t_2)\right\} < c_2, \quad t_1 \in \left[-d \quad 0\right], \ t_2 \in (0 \quad T]. \tag{2.8}$$

Definition 2.3 (FTB). For a given time-constant $T > 0$, the filtering error (2.5) is stochastically finite-time bounded (FTB) with respect to $(c_1 \quad c_2 \quad T \quad R_i \quad W)$ if condition (2.8) holds.

Remark 2.4. Notice that FTB and FTS are open-loop concepts. FTS can be recovered as a particular case of FTB with $W = 0$ and FTS leads to the concept of FTB in the presence of external inputs. FTB implies finite-time stability, but the converse is not true. It is necessary to point out that Lyapunov stability and FTS are independent concepts. Different with the concept of Lyapunov stability [33–35] which is largely known to the control community, a stochastic MJLSs is FTS if, once we fix a finite time-interval [36, 37], its state remain within prescribed bounds during this time-interval. Moreover, an MJLS which is FTS may not be Lyapunov stochastic stability; conversely, a Lyapunov stochastically stable MJLS could be not FTS if its states exceed the prescribed bounds during the transients.

Definition 2.5 (Feng et al. [34], Mao [35]). Let $V(x(t), r_t, t > 0)$ be the stochastic positive functional; define its weak infinitesimal operator as

$$\Im V(x(t), r_t = i, t) = \lim_{\Delta t\to 0}\frac{1}{\Delta t}\left[\mathbf{E}\{V(x(t+\Delta t), r_{t+\Delta t}, t+\Delta t) \mid x(t), r_t = i\} - V(x(t), r_t = i, t)\right]. \tag{2.9}$$

Definition 2.6. For the filtering error MJLSs (2.5), if there exist filter parameters A_{fi}, B_{fi}, and C_{fi}, and a positive scalar γ, such that (2.5) is FTB and under the zero-valued initial condition, the system output error satisfies the following cost function inequality for $T > 0$ with attenuation $\gamma > 0$ and for all admissible $w(t)$ with the constraint condition (2.7),

$$J = \mathbf{E}\left\{\|r(t)\|_\infty^2\right\} - \gamma^2\|d(t)\|_2^2 < 0, \tag{2.10}$$

where $\mathbf{E}\{\|r(t)\|_\infty^2\} = \mathbf{E}\{\sup_{t\in[0 \quad T]}[r^T(t)r(t)]\}$, $\|w(t)\|_2^2 = \int_0^T w^{\mathrm{T}}(t)w(t)dt$.

Then, the filter (2.3) is called the stochastic finite-time L_2-L_∞ filter of time-delay dynamic MJLSs (2.2) with γ-disturbance attenuation.

Remark 2.7. In stochastic finite-time L_2-L_∞ filtering process, the unknown noises $w(t)$ are assumed to be arbitrary deterministic signals of bounded energy and the problem of this paper is to design a filter that guarantees a prescribed bounded for the finite-time interval induced L_2-L_∞ norm of the operator from the unknown noise inputs $w(t)$ to the output error $r(t)$, that is, the designed stochastic finite-time L_2-L_∞ filter is supposed to satisfy inequality (2.10) with attenuation γ.

3. Finite-Time L_2-L_∞ Filtering for MJLSs

In this section, we will study the stochastic finite-time L_2-L_∞ filtering problem for time-delay dynamic MJLSs (2.2).

Theorem 3.1. *For a given time-constant $T > 0$, the filtering error MJLSs* (2.5) *are stochastically FTB with respect to $(c_1 \quad c_2 \quad T \quad R_i \quad W)$ and has a prescribed L_2-L_∞ performance level $\gamma > 0$ if there exist a set of mode-dependent symmetric positive-definite matrices $\overline{P}_i \in \Re^{2n\times 2n}$ and symmetric positive-definite matrix $\overline{Q} \in \Re^{2n\times 2n}$, satisfying the following matrix inequalities for all $i \in M$,*

$$\begin{bmatrix} \Lambda_i - \alpha\overline{P}_i & \overline{P}_i\overline{A}_{di} & \overline{P}_i\overline{B}_i \\ * & -\overline{Q} & 0 \\ *_i & * & -I \end{bmatrix} < 0, \tag{3.1}$$

$$\overline{C}_i^T\overline{C}_i < \gamma^2\overline{P}_i, \tag{3.2}$$

$$c_1\left(\sigma_P + d\sigma_Q\right) + \frac{W}{\alpha}\left(1 - e^{-\alpha T}\right) < e^{-\alpha T}c_2\sigma_p, \tag{3.3}$$

where $\Lambda_i = \overline{A}_i^T\overline{P}_i + \overline{P}_i\overline{A}_i + \overline{Q} + \sum_{j=1}^N \pi_{ij}\overline{P}_j$, $\underline{\sigma}_P = \min_{i\in M}\sigma_{\min}(\widetilde{P}_i)$, $\overline{\sigma}_P = \max_{i\in M}\sigma_{\max}(\widetilde{P}_i)$, $\sigma_Q = \max_{i\in M}\sigma_{\max}(Q_i)$, $Q_i = R_i^{-1/2}\overline{Q}R_i^{-1/2}$, and $\widetilde{P}_i = R_i^{-1/2}\overline{P}_iR_i^{-1/2}$.

Proof. For the given symmetric positive-definite matrices $\overline{P}_i \in \Re^{2n\times 2n}$ and $\overline{Q} \in \Re^{2n\times 2n}$, we define the following stochastic Lyapunov-Krasovskii functional as

$$V(\overline{x}(t), i) = \overline{x}^T(t)\overline{P}_i\overline{x}(t) + \int_{t-d}^{t} \overline{x}^T(\varsigma)\ \overline{Q}\ \ \overline{x}(\varsigma)d\varsigma. \tag{3.4}$$

Then referring to Definition 2.5 and along the trajectories of the resulting closed-loop MJLSs (2.7), we can derive the corresponding time derivative of $V(\overline{x}(t), i)$ as

$$\begin{aligned} \Im V(\overline{x}(t),\ i) = {} & \overline{x}^T(t)\Lambda_i\overline{x}(t) + 2\overline{x}^T(t)\overline{P}_i\overline{A}_{di}\overline{x}(t-d) \\ & + 2\overline{x}^T(t)\overline{P}_i\overline{B}_iw(t) - \overline{x}^T(t-d)\overline{Q}\ \overline{x}(t-d). \end{aligned} \tag{3.5}$$

Considering the L_2-L_∞ filtering performance for the dynamic filtering error system (2.5), we introduce the following cost function by Definition 2.6 with $t \geq 0$,

$$J_1(t) = \mathbf{E}\{\Im V(\overline{x}(t),\ i)\} - \alpha\mathbf{E}\{\ V(\overline{x}(t),\ i)\} - w^T(t)w(t). \tag{3.6}$$

According to relation (3.1), it follows that $J_1(t) < 0$, that is,

$$\mathbf{E}\{\Im V(\overline{x}(t),\ i)\} < \alpha\mathbf{E}\{V(\overline{x}(t),\ i)\} + w^T(t)w(t). \tag{3.7}$$

Then, multiplying the above inequality by $e^{-\alpha t}$, we have

$$\Im\{e^{-\alpha t}\mathbf{E}[V(\overline{x}(t),\ i)]\} < e^{-\alpha t}w^T(t)w(t). \tag{3.8}$$

In the following, we assume zero initial condition, that is, $\overline{x}(t) = 0$, for $t \in [-d \quad 0]$, and integrate the above inequality from 0 to T; then

$$e^{-\alpha T}\mathbf{E}[V(\overline{x}(T), i)] < \int_0^T e^{-\alpha t}w^T(t)w(t)dt. \tag{3.9}$$

Recalling to the defined Lyapunov-Krasovskii functional, it can be verified that,

$$\mathbf{E}\left\{\overline{x}^T(T)\overline{P}_i\overline{x}(T)\right\} < \mathbf{E}[V(\overline{x}(T), i)] < \int_0^T e^{-\alpha t}w^T(t)w(t)dt. \tag{3.10}$$

By (3.2) and within the finite-time interval $[0 \quad T]$, we can also get

$$\begin{aligned}\mathbf{E}\left\{r^T(T)r(T)\right\} &= \mathbf{E}\left\{\overline{x}^T(T)\overline{C}_i^T\overline{C}_i\overline{x}(T)\right\} < \gamma^2\mathbf{E}\left\{\overline{x}^T(T)\overline{P}_i\overline{x}(T)\right\} \\ &= \gamma^2 V(\overline{x}(T),\ i) < \gamma^2 e^{\alpha T}\int_0^T e^{-\alpha t}w^T(t)w(t)dt < \gamma^2 e^{\alpha T}\int_0^T w^T(t)w(t)dt.\end{aligned} \tag{3.11}$$

Therefore, the cost function inequality (2.10) can be guaranteed by setting $\overline{\gamma} = \sqrt{e^{\alpha T}}\,\gamma$, which implies $J = \mathrm{E}\{\|r(t)\|_\infty^2\} - \overline{\gamma}^2\|w(t)\|_2^2 < 0$.

On the other hand, by integrating the above inequality (3.8) between 0 to $t \in [0 \quad T]$, it yields

$$e^{-\alpha t}\mathbf{E}\{V(\overline{x}(t), i)\} - \mathbf{E}\{V\{\overline{x}(0), r_t = \xi(0)\}\} < \int_0^t e^{-\alpha s}w^T(t)w(t)ds. \tag{3.12}$$

Denote $\widetilde{P}_i = R_i^{-1/2}\overline{P}_i R_i^{-1/2}$, $Q_i = R_i^{-1/2}\overline{Q}R_i^{-1/2}$, $\underline{\sigma}_P = \min_{i\in M}\sigma_{\min}(\widetilde{P}_i)$, $\overline{\sigma}_P = \max_{i\in M}\sigma_{\max}(\widetilde{P}_i)$, and $\sigma_Q = \max_{i\in M}\sigma_{\max}(Q_i)$. Note that $\alpha > 0$, $0 \le t \le T$; then

$$\begin{aligned}\mathbf{E}\left\{\overline{x}^T(T)\overline{P}_i\overline{x}(T)\right\} \le \mathbf{E}\{\ V(\overline{x}(t), \quad i)\} &< e^{\alpha t}\mathbf{E}\{V(\overline{x}(0),\ r_t = \xi(0))\} + e^{\alpha t}\int_0^t e^{-\alpha s}w^T(s)w(s)ds \\ &< e^{\alpha t}\mathbf{E}\{V(\overline{x}(t),\ r_t)\}|_{t\in[-d \quad 0]} + e^{\alpha t}W\int_0^t e^{-\alpha s}ds \\ &< e^{\alpha T}\left[c_1(\sigma_P + d \quad \sigma_Q) + \frac{W}{\alpha}\left(1 - e^{-\alpha T}\right)\right].\end{aligned} \tag{3.13}$$

From the selected stochastic Lyapunov-Krasovskii function, we can obtain

$$\mathbf{E}\left[x^T(t)\overline{P}_i x(t)\right] \geq \sigma_p \mathbf{E}\left[x^T(t)R_i x(t)\right]. \tag{3.14}$$

Then we can get

$$\mathbf{E}\left[x^T(t)R_i x(t)\right] < \frac{e^{\alpha T}\left[c_1\left(\sigma_P + d\quad \sigma_Q\right) + (W/\alpha)\left(1 - e^{-\alpha T}\right)\right]}{\sigma_p} \tag{3.15}$$

which implies $\mathbf{E}[x^T(t)R_i x(t)] < c_2$ for $\forall t \in [0 \quad T]$. This completes the proof. □

Theorem 3.2. *For a given time-constant $T > 0$, the filtering error dynamic MJLSs* (2.5) *are FTB with respect to* $(c_1 \quad c_2 \quad T \quad R_i \quad W)$ *with* $R_i = \operatorname{diag}\{V_i \quad V_i\}$ *and has a prescribed L_2-L_∞performance level $\gamma > 0$ if there exist a set of mode-dependent symmetric positive-definite matrices $P_i \in \Re^{n\times n}$, symmetric positive-definite matrix $Q \in \Re^{n\times n}$, a set of mode-dependent matrices X_i, Y_i, and C_{fi} and positive scalars σ_1, σ_2 satisfying the following matrix inequalities for all $i \in M$,*

$$\begin{bmatrix} \Lambda_{1i} & * & P_i A_{di} & 0 & P_i B_i \\ \Lambda_{2i} & \Lambda_{3i} & 0 & P_i A_{di} & P_i B_i - Y_i D_i \\ * & * & -Q & 0 & 0 \\ * & * & * & -Q & 0 \\ * & * & * & * & -I \end{bmatrix} < 0, \tag{3.16}$$

$$\begin{bmatrix} P_i & 0 & L_i^T - C_{fi}^T \\ * & P_i & C_{fi}^T \\ * & * & \gamma^2 I \end{bmatrix} > 0, \tag{3.17}$$

$$V_i < P_i < \sigma_1 V_i, \tag{3.18}$$

$$0 < Q < \sigma_2 V_i, \tag{3.19}$$

$$c_1\sigma_1 + c_1 d\sigma_2 + \frac{W}{\alpha}\left(1 - e^{-\alpha T}\right) < e^{-\alpha T}c_2, \tag{3.20}$$

where $\Lambda_{1i} = A_i^T P_i + P_i A_i + Q + \sum_{j=1}^N \pi_{ij}P_j - \alpha\ P_i$, $\Lambda_{2i} = P_i A_i - X_i - Y_i C_i$, *and* $\Lambda_{3i} = X_i^T + X_i + Q + \sum_{j=1}^N \pi_{ij}P_j - \alpha\ P_i$.

Moreover, the suitable filter parameters can be given as

$$A_{fi} = P_i^{-1}X_i, \qquad B_{fi} = P_i^{-1}Y_i, \qquad C_{fi} = C_{fi}. \tag{3.21}$$

Proof. For convenience, we set $\overline{P}_i = \operatorname{diag}\{P_i, P_i\}$, $\overline{Q} = \operatorname{diag}\{Q, Q\}$. Then inequalities (3.1) and (3.2) are equivalent to LMIs (3.16) and (3.17) by letting $X_i = P_i A_{fi}$, $Y_i = P_i B_{fi}$.On the other hand, by setting $R_i = \operatorname{diag}\{V_i \quad V_i\}$, LMIs (3.18) and (3.19) imply that

$$1 < \underline{\sigma}_P = \min_{i \in M} \sigma_{\min}\left(\tilde{P}_i\right), \qquad \overline{\sigma}_P = \max_{i \in M} \sigma_{\max}\left(\tilde{P}_i\right) < \sigma_1, \qquad \sigma_Q = \max_{i \in M} \sigma_{\max}(Q_i) \leq \sigma_2. \quad (3.22)$$

Then recalling condition (3.3), we can get LMI (3.20). This completes the proof. □

Remark 3.3. It can be seen that if we choose the infinite time-interval, that is, $T \to \infty$, the main results in Theorems 3.1 and 3.2 can reduce to conclusions of regular L_2-L_∞ filtering. And other filtering schemes, such as Kalman, H_∞, and H_2 filtering of stochastic jump systems can be also handled, referring to [9–13, 29, 32]. When the delays in MJLSs (2.2) satisfy $d = 0$, it reduces to a delay-free system. We can immediately get the corresponding results implied in Theorems 3.1 and 3.2 by choosing the stochastic Lyapunov-Krasovskii functional as $V(\overline{x}(t), i) = \overline{x}^T(t)\overline{P}_i\overline{x}(t)$ and following the similar proofs.

4. Extension to Uncertain MJLSs

It has been recognized that the unknown disturbances and parameter uncertainties are inherent features of many physical process and often encountered in engineering systems, their presences must be considered in realistic filter design. For these, we consider the following stochastic time-delay MJLSs with uncertain parameters,

$$\begin{aligned}
\dot{x}(t) &= [A(r_t) + \Delta A(r_t, t)]x(t) + [A_d(r_t) + \Delta A_d(r_t, t)]x(t-d) + B(r_t)w(t), \\
y(t) &= C(r_t)x(t) + D(r_t)w(t), \\
z(t) &= L(r_t)x(t), \\
x(t) &= \lambda(t), \quad r_t = \xi(t), \quad t \in \left[t_0 - d \quad t_0\right].
\end{aligned} \quad (4.1)$$

Assumption 2. *The time-varying but norm-bounded uncertainties $\Delta A(r_t, t)$ and $\Delta A_d(r_t, t)$ satisfy*

$$\left[\Delta A(r_t, t) \quad \Delta A_d(r_t, t)\right] = M_i \Gamma_i(t) \left[N_{1i} \quad N_{2i}\right], \quad (4.2)$$

where M_i, N_{1i}, and N_{2i} are known real constant matrices of appropriate dimensions, $\Gamma_i(t)$ is unknown, time-varying matrix function satisfying $\|\Gamma_i(t)\|_2 \leq 1$, and the elements of $\Gamma_i(t)$ are Lebesgue measurable for any $i \in M$.

Remark 4.1. In condition (4.2), M_i is chosen as a full row rank matrix. And the parameter uncertainty structure is an extension of the admissible condition. In fact, it is always impossible to obtain the exact mathematical model of the practical dynamics due to environmental noises, complexity process, time-varying parameters, and many measuring difficulties, and so forth. These motivate us to consider system (4.1) containing uncertainties $\Delta A(r_t, t)$ and $\Delta A_d(r_t, t)$. Moreover, the uncertainties $\Delta A(r_t, t)$ and $\Delta A_d(r_t, t)$within (4.2) reflect the inexactness in mathematical modeling of jump dynamical systems. To simplify the study, $\Delta A(r_t, t)$ and $\Delta A_d(r_t, t)$ can be abbreviated as ΔA_i and ΔA_{di}. It is necessary to point out that the unknown mode-dependent matrix $\Gamma_i(t)$ in (4.2) can also be allowed to be state-dependent, that is, $\Gamma_i(t) = \Gamma_i(t,\ x(t))$, as long as $\|\Gamma_i(t,\ x(t))\| \le 1$ is satisfied.

For this case, we can get the following filtering error system by letting $\overline{x}^T(t) = [\ x^T(t)\ \ e^T(t)\ ]$:

$$\dot{\overline{x}}(t) = \overline{A}_i\overline{x}(t) + \overline{A}_{di}\overline{x}(t-d) + \overline{B}_i w(t), \\ r(t) = \overline{C}_i\overline{x}(t), \tag{4.3}$$

where

$$\overline{A}_i = \begin{bmatrix} A_i + \Delta A_i & 0 \\ A_i + \Delta A_i - A_{fi} - B_{fi}C_i & A_{fi} \end{bmatrix}, \qquad \overline{A}_{di} = \begin{bmatrix} A_{di} + \Delta A_{di} & 0 \\ \Delta A_{di} & A_{di} \end{bmatrix}, \\ \overline{B}_i = \begin{bmatrix} B_i \\ B_i - B_{fi}D_i \end{bmatrix}, \qquad \overline{C}_i = \begin{bmatrix} L_i - C_{fi} & C_{fi} \end{bmatrix}. \tag{4.4}$$

Lemma 4.2 (Wang et al. [38]). *Let T, M, and N be real matrices with appropriate dimensions. Then for all time-varying unknown matrix function $F(t)$ satisfying $\|F(t)\| \le 1$, the following relation*

$$T + MF(t)N + [MF(t)N]^T < 0 \tag{4.5}$$

holds if and only if there exists a positive scalar $\alpha > 0$, such that

$$T + \alpha^{-1}MM^T + \alpha N^T N < 0. \tag{4.6}$$

By following the similar lines and the main proofs of Theorems 3.1 and 3.2 and using the above Lemma 4.2, one can get the results stated as follows.

Theorem 4.3. *For a given time-constant $T > 0$, the filtering error MJLSs (4.3) with uncertainties are stochastically FTB with respect to $(c_1\quad c_2\quad T\quad V_i\quad W)$ and has a prescribed L_2-L_∞ performance level $\gamma > 0$ if there exist a set of mode-dependent symmetric positive-definite matrices $P_i \in \Re^{n\times n}$, symmetric positive-definite matrix $Q \in \Re^{n\times n}$, a set of mode-dependent matricesX_i, Y_i, and C_{fi} and positive scalars σ_1, σ_1 and ε_i satisfying LMIs (3.17)–(3.20), and the following matrix inequalities for all $i \in M$,*

$$\begin{bmatrix} \Lambda_{1i} + \varepsilon_i N_{1i}^T N_{1i} & * & P_iA_{di} + \varepsilon_i N_{1i}^T N_{2i} & 0 & P_iB_i & P_iM_i \\ \Lambda_{2i} & \Lambda_{3i} & 0 & P_iA_{di} & P_iB_i - Y_iD_i & P_iM_i \\ * & * & -Q + \varepsilon_i N_{2i}^T N_{2i} & 0 & 0 & 0 \\ * & * & * & -Q & 0 & 0 \\ * & * & * & * & -I & 0 \\ * & * & * & * & * & -\varepsilon_i I \end{bmatrix} < 0. \tag{4.7}$$

And the suitable stochastic finite-time L_2-L_∞ filter can be derived by (3.21).

Remark 4.4. Theorems 3.2 and 4.3 have presented the sufficient condition of designing the stochastic finite-time L_2-L_∞filter of time-delay MJLSs. Notice that the coupled LMIs (3.16)–(3.20) (or LMIs (4.7), (3.17)–(3.20)) are with respect to P_i, Q, V_i, X_i, Y_i, C_{fi}, c_1, c_2, σ_1, σ_2, T, W, γ^2, and ε_i. Therefore, for given V_i, c_1, T, and W, we can take γ^2 as optimal variable, that is, to obtain an optimal stochastic finite-time L_2-L_∞filter, the attenuation lever γ^2 can be reduced to the minimum possible value such that LMIs (3.16)–(3.20) (or LMIs (4.7), (3.17)–(3.20)) are satisfied. The optimization problem [39] can be described as follows:

$$\begin{gathered}\min_{P_i, X_i, Y_i, C_{fi}, \sigma_1, \sigma_2, c_2,\ \varepsilon_i, \rho} \rho \\ \text{s. t. LMIs (3.16)–(3.20)} \quad \text{or} \quad \text{LMI s (4.7), (3.17)–(3.20) with } \rho = \gamma^2. \end{gathered} \tag{4.8}$$

Remark 4.5. As we did in previous Remark 4.4, we can also fix γ and look for the optimal admissible c_1 or c_2 guaranteeing the stochastically finite-time boundedness of desired filtering error dynamic properties.

5. Numeral Examples

Example 5.1. Consider a class of constant time-delay MJLSs with parameters described as follows:

Mode 1

$$\begin{gathered} A_1 = \begin{bmatrix} -1 & 2 \\ -3 & -2 \end{bmatrix}, \qquad A_{d1} = \begin{bmatrix} -0.2 & 0 \\ -0.1 & -0.2 \end{bmatrix}, \qquad B_1 = \begin{bmatrix} -0.2 \\ 0.1 \end{bmatrix}, \\ C_1 = \begin{bmatrix} 1 & 0.5 \end{bmatrix}, \qquad D_1 = [0.1], \qquad L_1 = \begin{bmatrix} 0.6 & 1 \end{bmatrix}; \end{gathered} \tag{5.1}$$

Mode 2

$$\begin{gathered} A_2 = \begin{bmatrix} 0 & 3 \\ -1 & -2 \end{bmatrix}, \qquad A_{d2} = \begin{bmatrix} 0 & -0.1 \\ 0.2 & 0.3 \end{bmatrix}, \qquad B_2 = \begin{bmatrix} 0.1 \\ -0.2 \end{bmatrix}, \\ C_2 = \begin{bmatrix} 1 & 1 \end{bmatrix}, \qquad D_2 = [-0.2], \qquad L_2 = \begin{bmatrix} 0.2 & -1 \end{bmatrix}. \end{gathered} \tag{5.2}$$

Let the transition rate matrix be $\Pi = \left[\begin{smallmatrix} -3 & 3 \\ 4 & -4 \end{smallmatrix}\right]$. With the initial value for $\alpha = 0.5$, $W = 2$, $T = 4$, and $V_i = I_2$, we fix $\gamma = 0.8$ and look for the optimal admissible c_2 of different c_1 guaranteeing the stochastically finite-time boundedness of desired filtering error dynamic properties. Table 1 and Figure 1, respectively, give the optimal minimal admissible c_2 with different initial upper bound c_1.

Table 1: The optimal minimal admissible c_2 with different initial upper bound c_1.

c_1	0	1	2	4	8	12	16	18	20
c_2	25.5562	25.5572	25.5566	25.5585	25.5600	25.5610	25.5615	25.5672	25.5629

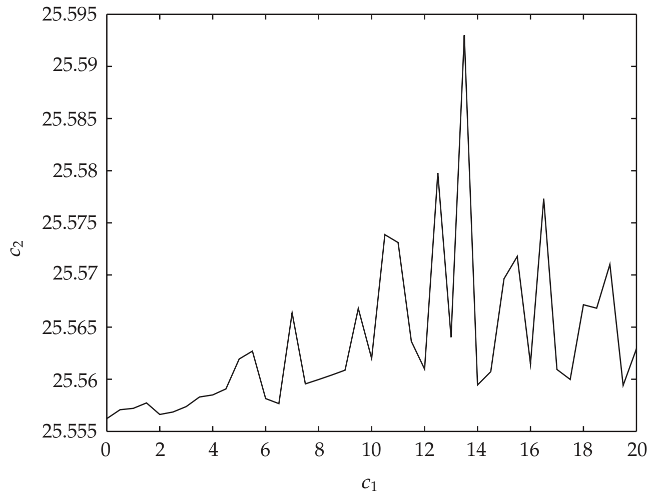

Figure 1: The optimal minimal upper bound c_2 with different initial c_1.

For $c_1 = 1$, we solve LMIs (3.16)–(3.20) by Theorem 3.2 and optimization algorithm (4.8) and get the following optimal L_2-L_∞ filters as

$$A_{f1} = \begin{bmatrix} -1.0695 & 0.3912 \\ -1.3394 & -4.2562 \end{bmatrix}, \qquad B_{f1} = \begin{bmatrix} -1.3705 \\ 3.2483 \end{bmatrix}, \qquad C_{f1} = \begin{bmatrix} -0.3 & 0.4 \end{bmatrix},$$
$$A_{f2} = \begin{bmatrix} -3.2169 & 8.7042 \\ 1.5785 & -8.0938 \end{bmatrix}, \qquad B_{f2} = \begin{bmatrix} 1.9832 \\ -2.6324 \end{bmatrix}, \qquad C_{f2} = \begin{bmatrix} 0.1 & -0.5 \end{bmatrix}. \tag{5.3}$$

And then, we can also get the attenuation lever as $\gamma = 0.0755$.

Example 5.2. Consider a class of constant time-delay MJLSs with uncertain parameters described as follows:

$$M_1 = \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}, \qquad N_{11} = \begin{bmatrix} 0.1 & 0 \end{bmatrix}, \qquad N_{12} = \begin{bmatrix} -0.1 & 0.12 \end{bmatrix},$$
$$M_2 = \begin{bmatrix} -0.1 \\ 0.1 \end{bmatrix}, \qquad N_{11} = \begin{bmatrix} 0.1 & -0.2 \end{bmatrix}, \qquad N_{12} = \begin{bmatrix} 0.1 & 0.3 \end{bmatrix}. \tag{5.4}$$

The modes, transition rate matrix, the matrices parameters and initial conditions are defined similarly as Example 5.1.

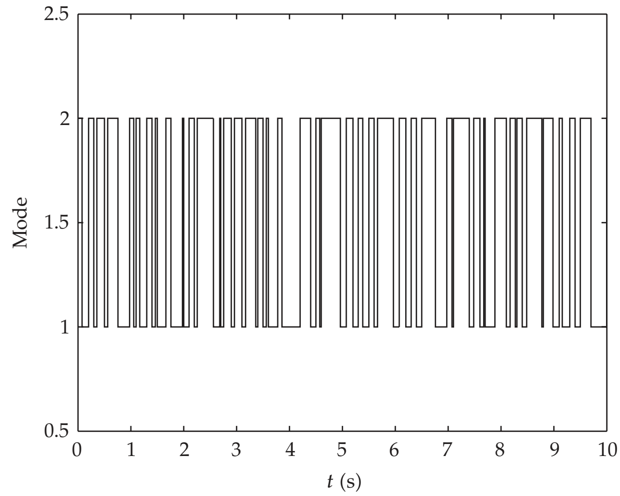

Figure 2: The estimation of changing between modes during the simulation with the initial mode 1.

By solving LMIs (4.7), (3.17)–(3.20) by Theorem 4.3 and Remark 4.4, we can get the optimal value $\gamma_{\min} = 0.0759$, and the mode-dependent optimized L_2-L_∞ filtering performance can be easily obtained as follows:

$$A_{f1} = \begin{bmatrix} -1.0520 & -0.3571 \\ -1.3063 & -4.1243 \end{bmatrix}, \qquad B_{f1} = \begin{bmatrix} -1.3418 \\ 3.2853 \end{bmatrix}, \qquad C_{f1} = \begin{bmatrix} -0.3 & 0.4 \end{bmatrix},$$
$$A_{f2} = \begin{bmatrix} -3.1664 & 8.6058 \\ 1.5604 & -8.0587 \end{bmatrix}, \qquad B_{f2} = \begin{bmatrix} 1.9745 \\ -2.6445 \end{bmatrix}, \qquad C_{f2} = \begin{bmatrix} 0.1 & -0.5 \end{bmatrix}. \tag{5.5}$$

In this work, the simulation time is selected as $t \in [\,0 \;\; 10\,]$. Assume the initial conditions are $x_1(0) = x_{f1}(0) = 1.0$, $x_2(0) = x_{f2}(0) = 0.8$ and $r_0 = 1$. The unknown inputs are selected as

$$w(t) = \begin{cases} 1.2e^{-0.2t}\sin(100t), & t \geq 0, \\ 0, & t < 0. \end{cases} \tag{5.6}$$

The simulation results of jump mode (the estimation of changing between modes during the simulation with the initial mode 1), the response of system states (real states and estimated states) and filtering output error are shown in Figures 2–5, which show the effective of the proposed approaches.

It is clear from Figures 3–5 that the estimated states can track the real states smoothly. Furthermore, the presented L_2-L_∞ filter guarantees a prescribed bounded for the induced finite-time L_2-L_∞ norm of the operator from the unknown disturbance to the filtering output error with attenuation $\gamma = 0.0759$, which illustrates the effectiveness of the proposed techniques.

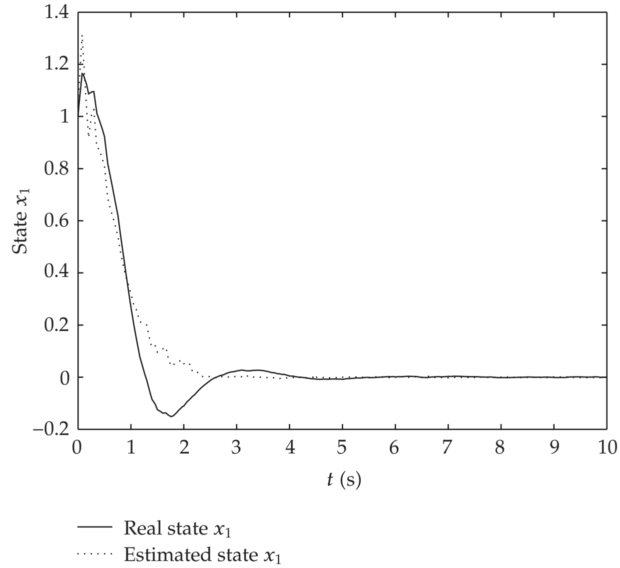

Figure 3: The response of the system state $x_1(t)$.

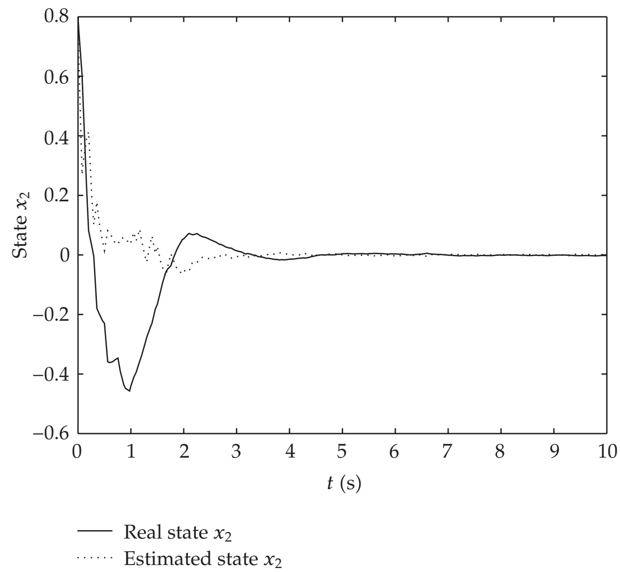

Figure 4: The response of the system state $x_2(t)$.

6. Conclusions

In the paper, we have studied the design of stochastic finite-time L_2-L_∞ filter for uncertain time-delayed MJLSs. It ensures the finite-time stability and finite-time boundedness for the filtering error dynamic MJLSs. By selecting the appropriate Lyapunov-Krasovskii function and applying matrix transformation and variable substitution, the main results are provided

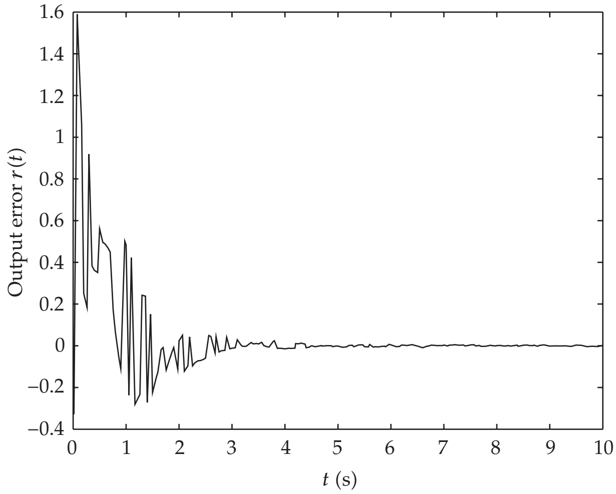

Figure 5: The response of the output error $r(t)$.

in terms of LMIs form. Simulation examples demonstrate the effectiveness of the developed techniques.

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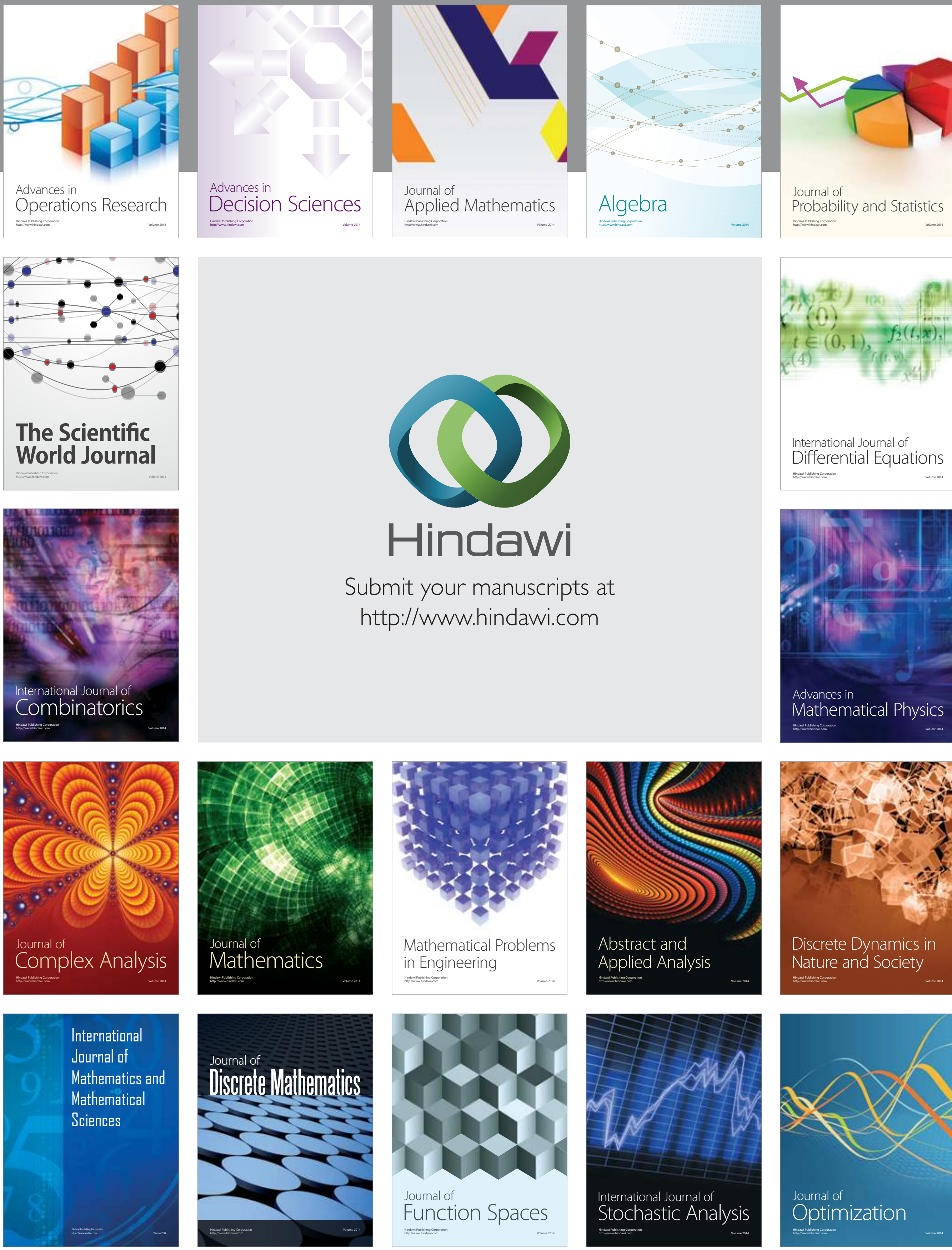
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