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OPTIMIZED STATE ESTIMATION FOR NONLINEAR DYNAMICAL NETWORKS SUBJECT TO FADING MEASUREMENTS AND STOCHASTIC COUPLING STRENGTH: AN EVENT-TRIGGERED COMMUNICATION MECHANISM

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This paper is concerned with the design of event-based state estimation algorithm for nonlinear complex networks with fading measurements and stochastic coupling strength. The event-based communication protocol is employed to save energy and enhance the network transmission efficiency, where the changeable event-triggered threshold is adopted to adjust the data transmission frequency. The phenomenon of fading measurements is described by a series of random variables obeying certain probability distribution. The aim of the paper is to propose a new recursive event-based state estimation strategy such that, for the admissible linearization error, fading measurements and stochastic coupling strength, a minimum upper bound of estimation error covariance is given by designing the estimator gain. Furthermore, the monotonicity relationship between the trace of the upper bound of estimation error covariance and the fading probability is pointed out from the theoretical aspect. Finally, a simulation example is used to show the effectiveness of developed state estimation algorithm.

Keywords: event-based communication protocol, fading measurements, stochastic coupling strength, nonlinear dynamical networks, monotonicity analysis

Classification: 93C10, 93E03, 93E10

1. INTRODUCTION

The last few decades have witnessed the increasing concerns on the developments of networked control systems (NCSs), where the main reason lies in that the NCSs have the advantages of flexibility, reliability, maneuverability and low cost owing to their applications in electric power grids, complex networks, and so on [6, 17, 18, 24, 42]. Regarding the complex networks, it is well recognized that the complex networks have been widely applied in the transportation networks, social networks, biological networks, chemical processes [1, 11, 19, 20, 26]. For example, the source estimation approaches have been given in [26] for complex networks with applications in public transportation field and a new secure distributed dynamic state estimation method has been given in [20] for smart grids with geographically separated sub-regions. In [11], a fault detection approach has

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been proposed via the horizontal visibility graph analysis-integrated complex networks, in which the presented method has been applied to the Tennessee Eastman process. Recently, many progresses have been reported on the dynamics analysis of complex networks within the networked circumstances [8, 22, 36, 37, 39, 43]. Among them, the designs of proper estimators have been appealing to estimate the immeasurable system state, which maintain the indispensable importance to understand the information of addressed networks. To mention a few, based on the linear matrix inequalities (LMIs), [36] and [37] have proposed the time-varying state estimation strategies to attenuate the undesirable influence from the incomplete measurements. Different from LMIs, the state estimation methods based on the minimum mean-square error criterion have been presented in [22] and [39] for nonlinear time-varying dynamical networks, where the coupling characteristics of the network nodes have been described in different ways in order to model the topological structure. As it is known to all, the inner/outer unreliable factors may lead to coupling diversities of complex network nodes, which deserve more research attentions.

With the rapid developments of network communication technology, a network channel is usually inserted to ensure the effectiveness of data transmissions [15, 16, 40]. Unfortunately, the channel bandwidth with limited communication capacity does not support large amounts of the data transmissions, hence the network congestion occurs frequently. In this case, the estimator/filter can receive the incomplete data only rather than all information from the sensor, which will inevitably reduce the accuracy of the proposed estimation algorithm [12, 28]. Therefore, it is imperative to study the state estimation problems with data loss or fading measurements and attenuate the caused influences by developing new estimation methods, see e. g. [23, 29, 30, 31, 33, 35, 38]. Specifically, a new time-varying recursive filtering strategy has been given in [33] for a class of 2-D time-varying systems under fading measurements, where a minimized upper bound of estimation error covariance has been obtained by designing the estimator gain in a proper way. Besides, a theoretical proof of the monotonicity between measurement degradation and estimation performance has been provided. In [29], a new state estimation scheme has been proposed for neural networks with multi-delays and random system parameters, where the incomplete measurements include the sensor saturations and signal quantization in a random switching way have been discussed. In addition, [31] and [35] have investigated the distributed recursive filtering problems with non-ideal measurements and the desired filtering gains have been given to achieve the minimized upper bound of filtering error covariance, where the boundedness analysis of filtering error and the monotonicity analysis on the trace of the minimum upper bound with respect to the occurrence probability have been conducted respectively. It should be mentioned that the occurrence of the incomplete measurements indeed degrades the desired performance requirements, which encourages us to do further discussions.

For the traditional time-driven strategy, the measured signals are usually transmitted at a fixed time, which indeed increases the channel transmission burden and overuses the limited network resources especially for NCSs. Apart from the estimation performance requirement, the energy consumption index should be considered. Compared with the conventional time-driven mechanism, the communication protocols show their advantages on saving the network resources and enhancing transmission flexibility including but not limited to Round–Robin (RR) protocol [7, 21] and event-based communication protocol [3, 9, 25, 32, 41]. Generally speaking, the information can be transmitted if the event generator function is satisfied with pre-defined triggered threshold. For example, the recursive state estimation issue has been addressed in [32] for linear time-varying systems involving event-driven strategy as well as packet dropouts, where the criteria of convergence and stability of the desired estimation error covariance have been presented. Unlike the event-triggered criterion with a constant triggered threshold, [10, 27, 34] have considered the effect from the time-varying event-driven condition onto the performance of the proposed state estimation algorithm. Regarding the state estimation problem for complex networks, [13, 14, 22] have presented some state estimation methods suitable for the time-varying circumstances, but those estimation approaches cannot save the communication resources efficiently and never evaluate the estimation performance. Very recently, the event-triggered estimation algorithms have been reported in [39, 40] for time-varying dynamical networks, where the adopted event-triggered condition depends on the absolute error of measurements and a fixed constant threshold. In order to further regulate the network communication and depict the node coupled characteristics, an event-triggered criterion with exponential-dependent threshold is introduced and the stochastic coupling strength is characterized by the inaccuracy coupling strength as well as the white noise, respectively. In particular, the influences of the stochastic coupling characteristics of network nodes, fading data and event-triggered protocol onto the corresponding state estimation method are examined, which constitutes the main motivation of the conducted topic. Overall, the purpose of this paper is to enrich the existing theoretical results on handling the state estimation problem for nonlinear time-varying complex networks.

Inspired by the discussions mentioned above, we aim to propose a new optimized state estimation algorithm against the event-based communication protocol, fading measurements and stochastic coupling strength. Compared with existing results, the main research challenges lie in that: (i) How to develop a new state estimation approach for addressed nonlinear complex networks in the simultaneous presence of the measurements degradation, stochastic coupling strength and event-triggered mechanism; (ii) How to better handle the negative effects from measurements degradations as well as stochastic coupling strength and utilize the effective information from other coupled nodes to improve the algorithm accuracy; (iii) How to evaluate the performance of new estimation scheme by presenting a proper analysis method? As a consequence, a locally optimal state estimation algorithm with performance evaluation is introduced to solve the above three questions, where a suboptimal upper bound of the estimation error covariance is derived and the desired estimator gain is designed via minimizing such obtained upper bound. The main contributions can be highlighted as follows: (1) a fairly comprehensive model is introduced to better reflect the nonlinear dynamical networks, which involves the fading measurements and stochastic coupling strength; (2) a recursive state estimation problem within the minimum mean-squared error sense is investigated for nonlinear dynamical systems, where the event-based communication protocol is considered for purpose of saving the limited communication resources; (3) the expression form of the time-varying estimator gain is provided in a recursive manner, where the corresponding state estimation method is applicable for online computations; and (4) the monotonicity analysis between the trace of minimized upper bound and the fading probability is demonstrated with rigorous mathematical proof.

Notations: The notations used in the paper are fairly standard. $\mathbb{R}^n$ and $\mathbb{R}^{m\times n}$ represent the n dimensional Euclidean space and the set of $m\times n$ real matrices, respectively. $\mathbb{E}\{\bullet\}$ stands for the mathematical expectation of a random variable $\bullet$. A^T, A^{-1} and $\mathrm{tr}(A)$ are the transpose, the inverse, the trace for real matrix A. $X > Y (X \geq Y)$ signifies that $X - Y$ is a positive definite (semi-definite) symmetric matrix. The $\mathrm{diag}\{X_1, X_2, \cdots, X_n\}$ denotes a diagonal matrix with $X_1, X_2, \cdots, X_n$ on the diagonal. $\circ$ refers to the Hadamard product defined as $[X \circ Y]_{ij} = X_{ij}Y_{ij}$. I and 0, respectively, stand for the identity matrix and the zero matrix with suitable dimensions.

2. PROBLEM FORMULATION AND PRELIMINARIES

In this paper, we consider the following array of nonlinear time-varying stochastic complex networks consisting of N coupled nodes:

$$\begin{aligned} x_{i,k+1} &= f(x_{i,k}) + \sum_{j=1}^{N}(\omega_{ij} + \zeta_{i,k}\Delta\omega_{ij})\Gamma x_{j,k} + B_{i,k}\varpi_{i,k} &(1)\\ y_{i,k} &= \Phi_{i,k}C_{i,k}x_{i,k} + \upsilon_{i,k} &(2)\end{aligned}$$

where $x_{i,k} \in \mathbb{R}^{n_1}$ denotes the state information and $y_{i,k} \in \mathbb{R}^{n_2}$ is the output measurement of the ith network node. $f(x_{i,k})$ is a continuously differentiable nonlinear function with a known form. $W = [\omega_{ij}]_{N\times N}$ is the coupling strength matrix and Γ denotes the inner coupling matrix. $|\Delta\omega_{ij}| \leq \delta_{ij}$ represents the uncertain coupling strength with $\delta_{ij} > 0$ being a scalar. $\varpi_{i,k}$ represents process noise with $\mathbb{E}\{\varpi_{i,k}\} = 0$ and $\mathbf{Var}\{\varpi_{i,k}\} = \mathfrak{Q}_{i,k}$. $\upsilon_{i,k}$ is measurement noise with $\mathbb{E}\{\upsilon_{i,k}\} = 0$ and $\mathbf{Var}\{\upsilon_{i,k}\} = \mathfrak{R}_{i,k}$. $\zeta_{i,k} \in \mathbb{R}$ is a zero-mean noise sequence satisfying $\mathbb{E}\{\zeta_{i,k}^2\} = 1$. $B_{i,k}$ and $C_{i,k}$ are known matrices with appropriate dimensions. $\Phi_{i,k} = \mathrm{diag}\{\phi_{i,k}^1, \phi_{i,k}^2, \cdots, \phi_{i,k}^{n_2}\}$ describes the sensor degradation with $\phi_{i,k}^l \in [a_i, b_i]$ $(l = 1, 2, \cdots, n_2)$ following the statistical characteristics $\mathbb{E}\{\phi_{i,k}^l\} = \bar{\phi}_{i,k}^l$ and $\mathbf{Var}\{\phi_{i,k}^l\} = \vec{\phi}_{i,k}^l$, where $0 \leq a_i \leq b_i \leq 1$.

The event-based communication protocol is employed in this paper to save the limited network resources and decrease dispensable energy consumptions. Particularly, the following transmission mechanism is adopted:

$$\sigma(y_{i,k}, \pi_{i,k}) = (y_{i,k} - y_{i,s_t})^T(y_{i,k} - y_{i,s_t}) - \pi_{i,k} > 0 \tag{3}$$

where y_{i,s_t} is the information received by estimator at the latest instant, $\pi_{i,k} = \tau_{i,1}e^{-\tau_{i,2}k} + \tau_{i,3}$ with $\tau_{i,1}$, $\tau_{i,2}$ and $\tau_{i,3}$ being known constants. In terms of (3), if $\sigma(y_{i,k}, \pi_{i,k}) > 0$, then the current measurement can be transmitted to the estimator side via the network. For all event-triggered instants s_t, the output signal received by the estimator can be denoted as:

$$\tilde{y}_{i,k} = y_{i,s_t}, \quad k \in \{s_t, s_t + 1, \cdots, s_{t+1} - 1\}.$$

Remark 2.1. Note that the information should be transmitted at each time step when using the traditionally time-triggered communication approach, thus there needs high communication resources. In (3), an event-triggered condition is introduced to regulate the network communication, where three parameters $\tau_{i,1}$, $\tau_{i,2}$ and $\tau_{i,3}$ are involved. According to (3), the information transmission frequency can be adjusted, which is particularly helpful for the situation of limited communication capacity. Besides, it should be mentioned that the traditionally time-triggered communication protocol is recovered when $\tau_{i,1} = \tau_{i,3} = 0$. Generally, there are some other event generator functions, see e. g. the function dependent on the absolute error of the innovation measurements and the generator function with respect to the dynamic event-triggered one, where different event-trigged conditions are provided and different transmission frequencies can be obtained accordingly. Thus, the efficiency of the network channel and the requirements of the communication capability would be different. Compared with the existing methods, the event generator function in (3) has a simple way and includes adjustment threshold parameters, thereby possibly providing additional flexibility for dealing with the addressed state estimation problem. On the other hand, it should be mentioned that the RR protocol is a periodic protocol and provides a communication scheduling that the node is given access to utilize the communication channel in a circle manner with fixed period. Compared with the RR protocol, the measurement $y_{i,k}$ can be transmitted via the adopted event-based communication protocol provided that the event generator function in (3) is satisfied, which represents a new transmission way.

Next, the following recursive state estimator is constructed:

$$\hat{x}_{i,k+1|k} = f(\hat{x}_{i,k|k}) + \sum_{j=1}^{N} \omega_{ij} \Gamma \hat{x}_{j,k|k} \tag{4}$$

$$\hat{x}_{i,k+1|k+1} = \hat{x}_{i,k+1|k} + K_{i,k+1} \left(\tilde{y}_{i,k+1} - \bar{\Phi}_{i,k+1} C_{i,k+1} \hat{x}_{i,k+1|k} \right) \tag{5}$$

where $\hat{x}_{i,k+1|k}$ is the prediction state of $x_{i,k}$ and $\hat{x}_{i,k|k}$ denotes the state estimation. $\bar{\Phi}_{i,k+1} = \mathbb{E}\{\Phi_{i,k+1}\}$, and $K_{i,k+1}$ is an estimator gain matrix to be designed.

Define the prediction error $e_{i,k+1|k} = x_{i,k+1} - \hat{x}_{i,k+1|k}$ and estimation error $e_{i,k+1|k+1} = x_{i,k+1} - \hat{x}_{i,k+1|k+1}$. Accordingly, $\mathfrak{P}_{i,k+1|k} = \mathbb{E}\{e_{i,k+1|k} e^T_{i,k+1|k}\}$ represents the prediction error covariance and $\mathfrak{P}_{i,k+1|k+1} = \mathbb{E}\{e_{i,k+1|k+1} e^T_{i,k+1|k+1}\}$ is the estimation error covariance, respectively. This paper is devoted to construct the estimator as in (4) and (5) such that 1) there exists a positive definite matrix $X_{i,k+1|k+1}$ guaranteeing $\mathfrak{P}_{i,k+1|k+1} \leq X_{i,k+1|k+1}$; 2) the $K_{i,k+1}$ with a specific form is given to ensure the existence of minimal value of $\mathrm{tr}(X_{i,k+1|k+1})$; 3) the monotonic relationship between $\mathrm{tr}(X_{i,k+1|k+1})$ and fading probability $\bar{\phi}^l_{i,k}$ is discussed.

Remark 2.2. As is known to all, all nodes of the complex dynamical networks are coupled and there exist the interactions, where the connection relationship is described by the coupling strength matrix and the inner coupling matrix. Note that most of the existing results regarding the complex dynamical networks have considered the deterministic coupling strength matrix, hence we consider the uncertain coupling strength in a random occurrence manner and characterize the potential modelling errors in order to better reflect the connection between different nodes. In particular, both $\zeta_{i,k}$ and $\Delta\omega_{ij}$ with known upper bound are utilized to depict the uncertain coupling strength, thereby further reflecting the engineering reality. On the other hand, there is a necessity to better quantify the effects of stochastic coupling strength, fading measurements as well as event-driven communication protocol and present an efficient estimation method accordingly. To fulfill this objective, a two-step state estimator is given in (4)−(5), which is constructed based on the transmitted measurements $\tilde{y}_{i,k+1}$ scheduled by the event-triggered protocol and the occurrence probability matrix $\bar{\Phi}_{i,k+1}$. In particular, the newly adopted state estimator includes the prediction and updating steps in order to improve the anti-interference capacity regarding those factors mentioned above. Moreover, the state estimator (4)−(5) is in a distributed way and then the proposed estimation method has an advantage on reducing the computation burdens.

3. DESIGN OF OPTIMIZED ESTIMATION SCHEME

In this section, the above mentioned goals will be achieved. Firstly, the prediction error is presented as follows:

$$e_{i,k+1|k} = f(x_{i,k}) - f(\hat{x}_{i,k|k}) + \sum_{j=1}^{N} \omega_{ij}\Gamma e_{j,k|k} + \sum_{j=1}^{N} \zeta_{i,k}\Delta\omega_{ij}\Gamma x_{j,k} + B_{i,k}\varpi_{i,k}.$$

Based on the Taylor formula, we have

$$f(x_{i,k}) = f(\hat{x}_{i,k|k}) + G_{i,k}e_{i,k|k} + o(|e_{i,k|k}|)$$

where $G_{i,k} = \frac{\partial f(x_{i,k})}{x_{i,k}}|_{x_{i,k}=\hat{x}_{i,k|k}}$ and $o(|e_{i,k|k}|)$ is the high-order term which is equivalent to $L_{i,k}\mathfrak{M}_{i,k}F_{i,k}e_{i,k|k}$ showed in [2] with $L_{i,k}$ and $F_{i,k}$ being known matrices, $\mathfrak{M}_{i,k}$ describes the linearization error satisfying $\mathfrak{M}_{i,k}\mathfrak{M}_{i,k}^T \leq I$. Then, we have

$$e_{i,k+1|k} = (G_{i,k} + L_{i,k}\mathfrak{M}_{i,k}F_{i,k})e_{i,k|k} + \sum_{j=1}^{N} \omega_{ij}\Gamma e_{j,k|k} + \sum_{j=1}^{N} \zeta_{i,k}\Delta\omega_{ij}\Gamma x_{j,k} + B_{i,k}\varpi_{i,k}. \quad (6)$$

Besides, one has

$$\begin{aligned} e_{i,k+1|k+1} \;=\; & \left(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1}\right) e_{i,k+1|k} - K_{i,k+1}\mathcal{Y}_{i,k+1} - K_{i,k+1}\upsilon_{i,k+1} \\ & - K_{i,k+1}\tilde{\Phi}_{i,k+1}C_{i,k+1}x_{i,k+1} \end{aligned} \quad (7)$$

where $\mathcal{Y}_{i,k+1} = \tilde{y}_{i,k+1} - y_{i,k+1}$ and $\tilde{\Phi}_{i,k+1} = \Phi_{i,k+1} - \bar{\Phi}_{i,k+1}$.

The following lemmas will play a significant role when presenting the main results.

Lemma 3.1. (Wen et al. [35]) For matrices A, B, C and D with appropriate dimensions, $U > 0$ is a symmetric matrix and $\iota > 0$ is an arbitrary scalar. In terms of the conditions $DD^T \leq I$ and $\iota^{-1}I - CUC^T > 0$ holding, the matrix inequality

$$(A + BDC)U(A + BDC)^T \leq A(U^{-1} - \iota C^TC)^{-1}A^T + \iota^{-1}BB^T$$

can be obtained.

Lemma 3.2. (Wen et al. [35]) Suppose that $Q = \operatorname{diag}\{q_1, q_2, \cdots, q_n\}$ is a random matrix and $R_{n\times n}$ is a real value matrix. Then there exists the following relationship

$$\mathbb{E}\{QRQ^T\} = \begin{bmatrix} \mathbb{E}\{q_1^2\} & \mathbb{E}\{q_1q_2\} & \cdots & \mathbb{E}\{q_1q_n\} \\ \mathbb{E}\{q_2q_1\} & \mathbb{E}\{q_2^2\} & \cdots & \mathbb{E}\{q_2q_n\} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{E}\{q_nq_1\} & \mathbb{E}\{q_nq_2\} & \cdots & \mathbb{E}\{q_n^2\} \end{bmatrix} \circ R$$

where $\circ$ represents the Hadamard product.

The following theorem further proposes the iteration equations of prediction error covariance and estimation error covariance.

Theorem 3.3. The prediction error covariance and estimation error covariance can be described as follows:

$$\begin{aligned} \mathfrak{P}_{i,k+1|k} &= (G_{i,k} + L_{i,k}\mathfrak{M}_{i,k}F_{i,k})\mathfrak{P}_{i,k|k}(G_{i,k} + L_{i,k}\mathfrak{M}_{i,k}F_{i,k})^T + \sum_{j=1}^{N}\sum_{d=1}^{N}\omega_{ij}\omega_{id} \\ &\quad \times\Gamma\mathbb{E}\left\{e_{j,k|k}e_{d,k|k}^T\right\}\Gamma^T + \sum_{j=1}^{N}\sum_{d=1}^{N}\Delta\omega_{ij}\Delta\omega_{id}\Gamma\mathbb{E}\left\{x_{j,k}x_{d,k}^T\right\}\Gamma^T \\ &\quad +B_{i,k}\mathfrak{Q}_{i,k}B_{i,k}^T + \mathfrak{G}_{i,k} + \mathfrak{G}_{i,k}^T \end{aligned} \tag{8}$$

and

$$\begin{aligned} \mathfrak{P}_{i,k+1|k+1} &= (I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})\mathfrak{P}_{i,k+1|k}(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})^T \\ &\quad +K_{i,k+1}\mathbb{E}\left\{\mathcal{Y}_{i,k+1}\mathcal{Y}_{i,k+1}^T\right\}K_{i,k+1}^T - \mathfrak{E}_{i,k} - \mathfrak{E}_{i,k}^T + \mathfrak{D}_{i,k} + \mathfrak{D}_{i,k}^T \\ &\quad +K_{i,k+1}\mathbb{E}\left\{\tilde{\Phi}_{i,k+1}C_{i,k+1}x_{i,k+1}x_{i,k+1}^TC_{i,k+1}^T\tilde{\Phi}_{i,k+1}^T\right\}K_{i,k+1}^T \\ &\quad +\mathfrak{F}_{i,k} + \mathfrak{F}_{i,k}^T + K_{i,k+1}\mathfrak{R}_{i,k+1}K_{i,k+1}^T \end{aligned} \tag{9}$$

where

$$\begin{aligned} \mathfrak{G}_{i,k} &= (G_{i,k} + L_{i,k}\mathfrak{M}_{i,k}F_{i,k})\sum_{j=1}^{N}\omega_{ij}\mathbb{E}\left\{e_{i,k|k}e_{j,k|k}^T\right\}\Gamma^T \\ \mathfrak{E}_{i,k} &= (I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})\mathbb{E}\left\{e_{i,k+1|k}\mathcal{Y}_{i,k+1}^T\right\}K_{i,k+1}^T \\ \mathfrak{D}_{i,k} &= K_{i,k+1}\mathbb{E}\left\{\mathcal{Y}_{i,k+1}x_{i,k+1}^TC_{i,k+1}^T\tilde{\Phi}_{i,k+1}^T\right\}K_{i,k+1}^T \\ \mathfrak{F}_{i,k} &= K_{i,k+1}\mathbb{E}\left\{\mathcal{Y}_{i,k+1}\upsilon_{i,k+1}^T\right\}K_{i,k+1}^T. \end{aligned}$$

Proof. According to equations (6) and (7), we can derive the prediction error covariance and estimation error covariance respectively. That is,

$$\mathfrak{P}_{i,k+1|k} = (G_{i,k} + L_{i,k}\mathfrak{M}_{i,k}F_{i,k})\mathfrak{P}_{i,k|k}(G_{i,k} + L_{i,k}\mathfrak{M}_{i,k}F_{i,k})^T + \sum_{j=1}^{N}\sum_{d=1}^{N}\omega_{ij}\omega_{id}$$

$$\times\Gamma\mathbb{E}\left\{e_{j,k|k}e_{d,k|k}^{T}\right\}\Gamma^{T}+\sum_{j=1}^{N}\sum_{d=1}^{N}\Delta\omega_{ij}\Delta\omega_{id}\Gamma\mathbb{E}\left\{x_{j,k}x_{d,k}^{T}\right\}\Gamma^{T}$$
$$+B_{i,k}\mathfrak{Q}_{i,k}B_{i,k}^{T}+\mathfrak{G}_{i,k}+\mathfrak{G}_{i,k}^{T}+\mathfrak{G}_{i,k}^{1}+\mathfrak{G}_{i,k}^{1^{T}}+\mathfrak{G}_{i,k}^{2}+\mathfrak{G}_{i,k}^{2^{T}}$$
$$+\mathfrak{G}_{i,k}^{3}+\mathfrak{G}_{i,k}^{3^{T}}+\mathfrak{G}_{i,k}^{4}+\mathfrak{G}_{i,k}^{4^{T}}+\mathfrak{G}_{i,k}^{5}+\mathfrak{G}_{i,k}^{5^{T}}$$

and

$$\begin{aligned}\mathfrak{P}_{i,k+1|k+1} &= (I-K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})\mathfrak{P}_{i,k+1|k}(I-K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})^{T}\\
&\quad+K_{i,k+1}\mathbb{E}\left\{\mathcal{Y}_{i,k+1}\mathcal{Y}_{i,k+1}^{T}\right\}K_{i,k+1}^{T}-\mathfrak{E}_{i,k}-\mathfrak{E}_{i,k}^{T}+\mathfrak{D}_{i,k}+\mathfrak{D}_{i,k}^{T}\\
&\quad+K_{i,k+1}\mathbb{E}\left\{\tilde{\Phi}_{i,k+1}C_{i,k+1}x_{i,k+1}x_{i,k+1}^{T}C_{i,k+1}^{T}\tilde{\Phi}_{i,k+1}^{T}\right\}K_{i,k+1}^{T}+\mathfrak{F}_{i,k}\\
&\quad+\mathfrak{F}_{i,k}^{T}+K_{i,k+1}\mathfrak{R}_{i,k+1}K_{i,k+1}^{T}-\mathfrak{F}_{i,k}^{1}-\mathfrak{F}_{i,k}^{1^{T}}-\mathfrak{F}_{i,k}^{2}-\mathfrak{F}_{i,k}^{2^{T}}+\mathfrak{F}_{i,k}^{3}+\mathfrak{F}_{i,k}^{3^{T}}\end{aligned}$$

where

$$\begin{aligned}\mathfrak{G}_{i,k}^{1} &= \sum_{j=1}^{N}(G_{i,k}+L_{i,k}\mathfrak{M}_{i,k}F_{i,k})\Delta\omega_{ij}\mathbb{E}\left\{\zeta_{i,k}e_{i,k|k}x_{j,k}^{T}\right\}\Gamma^{T}\\
\mathfrak{G}_{i,k}^{2} &= (G_{i,k}+L_{i,k}\mathfrak{M}_{i,k}F_{i,k})\mathbb{E}\left\{e_{i,k|k}\varpi_{i,k}^{T}\right\}B_{i,k}^{T}\\
\mathfrak{G}_{i,k}^{3} &= \sum_{j=1}^{N}\sum_{d=1}^{N}\omega_{ij}\Delta\omega_{id}\Gamma\mathbb{E}\left\{\zeta_{i,k}e_{j,k|k}x_{d,k}^{T}\right\}\Gamma^{T}\\
\mathfrak{G}_{i,k}^{4} &= \sum_{j=1}^{N}\omega_{ij}\Gamma\mathbb{E}\left\{e_{j,k|k}\varpi_{i,k}^{T}\right\}B_{i,k}^{T}\\
\mathfrak{G}_{i,k}^{5} &= \sum_{j=1}^{N}\Delta\omega_{ij}\Gamma\mathbb{E}\left\{\zeta_{i,k}x_{j,k}\varpi_{i,k}^{T}\right\}B_{i,k}^{T}\\
\mathfrak{F}_{i,k}^{1} &= \left(I-K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1}\right)\mathbb{E}\left\{e_{i,k+1|k}\upsilon_{i,k+1}^{T}\right\}K_{i,k+1}^{T}\\
\mathfrak{F}_{i,k}^{2} &= \left(I-K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1}\right)\mathbb{E}\left\{e_{i,k+1|k}x_{i,k+1}^{T}C_{i,k+1}^{T}\tilde{\Phi}_{i,k+1}^{T}\right\}K_{i,k+1}^{T}\\
\mathfrak{F}_{i,k}^{3} &= K_{i,k+1}\mathbb{E}\left\{\upsilon_{i,k+1}x_{i,k+1}^{T}C_{i,k+1}^{T}\tilde{\Phi}_{i,k+1}^{T}\right\}K_{i,k+1}^{T}.\end{aligned}$$

It's really simple to verify the facts that $\mathfrak{G}_{i,k}^{h}=0$ and $\mathfrak{F}_{i,k}^{t}=0$ ($h=1,2,3,4,5;t=1,2,3$). Thus, the assertions in the Theorem 3.3 are obtained and the proof is complete. □

Remark 3.4. Up to now, we have computed the prediction error covariance and estimation error covariance based on the corresponding definitions. However, the existence of some factors (e. g. linearization error, event-triggered mechanism, measurements degradation and uncertain coupling parameters) leads to the obstacles that the exact values of the prediction error covariance and the estimation error covariance can not be obtained. Therefore, we aim to find a sub-optimal upper bound of (9) by the stochastic analysis method. The next step is to obtain the minimal upper bound and design the estimator gain accordingly.

Theorem 3.5. Consider the prediction error covariance and estimation error covariance as in (8) and (9) respectively. Let μ_t $(t = 1, 2, \cdots, 6)$ and $\varepsilon_{i,k}$ be positive scalars. If the following iterative equations with initial condition $X_{0|0} = \mathfrak{P}_{0|0} > 0$

$$\begin{aligned} X_{i,k+1|k} &= (1+\mu_1)\left[G_{i,k}\left(X_{i,k|k}^{-1} - \varepsilon_{i,k}F_{i,k}^T F_{i,k}\right)^{-1} G_{i,k}^T + \varepsilon_{i,k}^{-1} L_{i,k} L_{i,k}^T\right] + B_{i,k}\mathfrak{Q}_{i,k}B_{i,k}^T \\ &\quad +(1+\mu_1^{-1})\vec{\omega}_{id}\sum_{j=1}^{N}\omega_{ij}\Gamma X_{j,k|k}\Gamma^T + \vec{\delta}_{id}\sum_{i=1}^{N}\delta_{ij}\Gamma\ddot{\Theta}_{j,k}\Gamma^T \end{aligned} \tag{10}$$

and

$$\begin{aligned} X_{i,k+1|k+1} &= (1+\mu_3)(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})X_{i,k+1|k}(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})^T \\ &\quad +(1+\mu_3^{-1}+\mu_4+\mu_5)\pi_{i,k+1}K_{i,k+1}K_{i,k+1}^T + (1+\mu_5^{-1})K_{i,k+1} \\ &\quad \times\mathfrak{R}_{i,k+1}K_{i,k+1}^T + (1+\mu_4^{-1})K_{i,k+1}\Big[\Omega_{i,k+1}\circ(C_{i,k+1}\ddot{\Sigma}_{i,k+1} \\ &\quad \times C_{i,k+1}^T)\Big]K_{i,k+1}^T \end{aligned} \tag{11}$$

under the constraint condition $\varepsilon_{i,k}^{-1}I - F_{i,k}X_{i,k|k}F_{i,k}^T > 0$ have positive definite symmetric solutions $X_{i,k+1|k}$ and $X_{i,k+1|k+1}$, then $X_{i,k+1|k+1}$ is an upper bound of $\mathfrak{P}_{i,k+1|k+1}$. In addition, the following estimator gain

$$\begin{aligned} K_{i,k+1} &= (1+\mu_3)X_{i,k+1|k}C_{i,k+1}^T\bar{\Phi}_{i,k+1}^T\Big\{(1+\mu_3)\bar{\Phi}_{i,k+1}C_{i,k+1}X_{i,k+1|k}C_{i,k+1}^T\bar{\Phi}_{i,k+1}^T \\ &\quad +(1+\mu_3^{-1}+\mu_4+\mu_5)\pi_{i,k+1}I + (1+\mu_4^{-1})\Omega_{i,k+1}\circ(C_{i,k+1}\ddot{\Sigma}_{i,k+1}C_{i,k+1}^T) \\ &\quad +(1+\mu_5^{-1})\mathfrak{R}_{i,k+1}\Big\}^{-1} \end{aligned} \tag{12}$$

can minimize $\mathrm{tr}(X_{i,k+1|k+1})$, where

$$\begin{aligned} \vec{\delta}_{id} &= \sum_{d=1}^{N}\delta_{id}, \quad \vec{\omega}_{id} = \sum_{d=1}^{N}\omega_{id} \\ \ddot{\Theta}_{j,k} &= (1+\mu_2)X_{j,k|k} + (1+\mu_2^{-1})\hat{x}_{j,k|k}\hat{x}_{j,k|k}^T \\ \ddot{\Sigma}_{i,k+1} &= (1+\mu_6)X_{i,k+1|k} + (1+\mu_6^{-1})\hat{x}_{i,k+1|k}\hat{x}_{i,k+1|k}^T \\ \Omega_{i,k+1} &= \mathrm{diag}\left\{\vec{\phi}_{i,k+1}^1, \vec{\phi}_{i,k+1}^2, \cdots, \vec{\phi}_{i,k+1}^{n_2}\right\}. \end{aligned} \tag{13}$$

P r o o f. Using the fundamental inequality, we can get

$$\begin{aligned} &\sum_{j=1}^{N}\sum_{d=1}^{N}\omega_{ij}\omega_{id}\Gamma\mathbb{E}\left\{e_{j,k|k}e_{d,k|k}^T\right\}\Gamma^T \\ \le\; &\frac{1}{2}\sum_{j=1}^{N}\sum_{d=1}^{N}\omega_{ij}\omega_{id}\Gamma\mathbb{E}\left\{e_{j,k|k}e_{j,k|k}^T + e_{d,k|k}e_{d,k|k}^T\right\}\Gamma^T \end{aligned}$$

$$= \quad \vec{\omega}_{id} \sum_{j=1}^{N} \omega_{ij} \Gamma \mathfrak{P}_{j,k|k} \Gamma^T \tag{14}$$

and

$$\begin{aligned} & \sum_{j=1}^{N} \sum_{d=1}^{N} \Delta\omega_{ij} \Delta\omega_{id} \Gamma \mathbb{E}\left\{x_{j,k} x_{d,k}^T\right\} \Gamma^T \\ \leq \quad & \frac{1}{2} \sum_{j=1}^{N} \sum_{d=1}^{N} \Delta\omega_{ij} \Delta\omega_{id} \Gamma \mathbb{E}\left\{x_{j,k} x_{j,k}^T + x_{d,k} x_{d,k}^T\right\} \Gamma^T \\ \leq \quad & \vec{\delta}_{id} \sum_{j=1}^{N} \delta_{ij} \Gamma \mathbb{E}\left\{x_{j,k} x_{j,k}^T\right\} \Gamma^T \end{aligned} \tag{15}$$

where $\vec{\omega}_{id}$ and $\vec{\delta}_{id}$ are defined in (13).

Based on the inequality $uv^T + vu^T \leq \mu uu^T + \mu^{-1} vv^T$ with v and u being column vectors and $\mu > 0$ being a scalar, we can obtain

$$\begin{aligned} \mathfrak{G}_{i,k} + \mathfrak{G}_{i,k}^T \quad \leq \quad & \mu_1 (G_{i,k} + L_{i,k} \mathfrak{M}_{i,k} F_{i,k}) \mathfrak{P}_{i,k|k} (G_{i,k} + L_{i,k} \mathfrak{M}_{i,k} F_{i,k})^T \\ & + \mu_1^{-1} \sum_{j=1}^{N} \sum_{d=1}^{N} \omega_{ij} \omega_{id} \Gamma \mathbb{E}\left\{e_{j,k|k} e_{d,k|k}^T\right\} \Gamma^T \end{aligned} \tag{16}$$

and

$$\mathbb{E}\left\{x_{j,k} x_{j,k}^T\right\} \quad \leq \quad (1+\mu_2) \mathfrak{P}_{j,k|k} + (1+\mu_2^{-1}) \hat{x}_{j,k|k} \hat{x}_{j,k|k}^T := \Theta_{j,k} \tag{17}$$

where μ_1 and μ_2 are positive scalars. Then, we have

$$\sum_{j=1}^{N} \sum_{d=1}^{N} \Delta\omega_{ij} \Delta\omega_{id} \Gamma \mathbb{E}\left\{x_{j,k} x_{d,k}^T\right\} \Gamma^T \quad \leq \quad \vec{\delta}_{id} \sum_{j=1}^{N} \delta_{ij} \Gamma \Theta_{j,k} \Gamma^T. \tag{18}$$

Taking (14), (16) and (18) into account simultaneously, we can arrive at

$$\begin{aligned} \mathfrak{P}_{i,k+1|k} \quad \leq \quad & (1+\mu_1)(G_{i,k} + L_{i,k} \mathfrak{M}_{i,k} F_{i,k}) \mathfrak{P}_{i,k|k} (G_{i,k} + L_{i,k} \mathfrak{M}_{i,k} F_{i,k})^T + B_{i,k} \mathfrak{Q}_{i,k} B_{i,k}^T \\ & + (1+\mu_1^{-1}) \vec{\omega}_{id} \sum_{j=1}^{N} \omega_{ij} \Gamma \mathfrak{P}_{j,k|k} \Gamma^T + \vec{\delta}_{id} \sum_{j=1}^{N} \delta_{ij} \Gamma \Theta_{j,k} \Gamma^T. \end{aligned} \tag{19}$$

Recalling the inequality $uv^T + vu^T \leq \mu uu^T + \mu^{-1} vv^T$, the following inequalities

$$\begin{aligned} -\mathfrak{E}_{i,k} - \mathfrak{E}_{i,k}^T \quad \leq \quad & \mu_3 (I - K_{i,k+1} \bar{\Phi}_{i,k+1} C_{i,k+1}) \mathfrak{P}_{i,k+1|k} (I - K_{i,k+1} \bar{\Phi}_{i,k+1} C_{i,k+1})^T \\ & + \mu_3^{-1} K_{i,k+1} \mathbb{E}\left\{\mathcal{Y}_{i,k+1} \mathcal{Y}_{i,k+1}^T\right\} K_{i,k+1}^T \end{aligned} \tag{20}$$

$$\begin{aligned} \mathfrak{D}_{i,k} + \mathfrak{D}_{i,k}^T \quad \leq \quad & \mu_4^{-1} K_{i,k+1} \mathbb{E}\left\{\tilde{\Phi}_{i,k+1} C_{i,k+1} x_{i,k+1} x_{i,k+1}^T C_{i,k+1}^T \tilde{\Phi}_{i,k+1}^T\right\} K_{i,k+1}^T \\ & + \mu_4 K_{i,k+1} \mathbb{E}\left\{\mathcal{Y}_{i,k+1} \mathcal{Y}_{i,k+1}^T\right\} K_{i,k+1}^T \end{aligned} \tag{21}$$

and

$$\mathfrak{F}_{i,k} + \mathfrak{F}_{i,k}^T \leq \mu_5 K_{i,k+1} \mathbb{E}\left\{\mathcal{Y}_{i,k+1}\mathcal{Y}_{i,k+1}^T\right\} K_{i,k+1}^T + \mu_5^{-1} K_{i,k+1} \mathfrak{R}_{i,k+1} K_{i,k+1}^T \quad (22)$$

hold, where μ_3, μ_4 and μ_5 are all positive scalars. Substituting the (20) − (22) into (9), one has

$$\begin{aligned} \mathfrak{P}_{i,k+1|k+1} \leq\ & (1+\mu_3)(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})\mathfrak{P}_{i,k+1|k}(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})^T \\ & +(1+\mu_3^{-1}+\mu_4+\mu_5)K_{i,k+1}\mathbb{E}\left\{\mathcal{Y}_{i,k+1}\mathcal{Y}_{i,k+1}^T\right\}K_{i,k+1}^T \\ & +(1+\mu_4^{-1})K_{i,k+1}\mathbb{E}\left\{\tilde{\Phi}_{i,k+1}C_{i,k+1}x_{i,k+1}x_{i,k+1}^T C_{i,k+1}^T \tilde{\Phi}_{i,k+1}^T\right\}K_{i,k+1}^T \\ & +(1+\mu_5^{-1})K_{i,k+1}\mathfrak{R}_{i,k+1}K_{i,k+1}^T. \end{aligned} \quad (23)$$

Noticing the event-based communication protocol employed in (3), we have

$$\mathbb{E}\left\{\mathcal{Y}_{i,k+1}\mathcal{Y}_{i,k+1}^T\right\} \leq \pi_{i,k+1} I. \quad (24)$$

Similar to (17), we obtain

$$\begin{aligned} \mathbb{E}\left\{x_{i,k+1}x_{i,k+1}^T\right\} \leq\ & (1+\mu_6)\mathfrak{P}_{i,k+1|k} + (1+\mu_6^{-1})\hat{x}_{i,k+1|k}\hat{x}_{i,k+1|k}^T \\ :=\ & \Sigma_{i,k+1} \end{aligned} \quad (25)$$

where $\mu_6 > 0$ is a scalar. In terms of (25) and Lemma 3.2, we obtain

$$\mathbb{E}\left\{\tilde{\Phi}_{i,k+1}C_{i,k+1}x_{i,k+1}x_{i,k+1}^T C_{i,k+1}^T \tilde{\Phi}_{i,k+1}^T\right\} \leq \Omega_{i,k+1} \circ (C_{i,k+1}\Sigma_{i,k+1}C_{i,k+1}^T) \quad (26)$$

where $\Omega_{i,k+1}$ is presented in (13). Consider the inequalities (24) and (26), we have

$$\begin{aligned} \mathfrak{P}_{i,k+1|k+1} \leq\ & (1+\mu_3)(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})\mathfrak{P}_{i,k+1|k}(I - K_{i,k+1}\bar{\Phi}_{i,k+1}C_{i,k+1})^T \\ & +(1+\mu_3^{-1}+\mu_4+\mu_5)\pi_{i,k+1}K_{i,k+1}K_{i,k+1}^T + (1+\mu_5^{-1})K_{i,k+1} \\ & \times\mathfrak{R}_{i,k+1}K_{i,k+1}^T + (1+\mu_4^{-1})K_{i,k+1}\Big[\Omega_{i,k+1} \circ (C_{i,k+1}\Sigma_{i,k+1} \\ & \times C_{i,k+1}^T)\Big]K_{i,k+1}^T. \end{aligned} \quad (27)$$

Combining (10), (11), (19) with (27) and utilizing the mathematical induction method, we can conclude that

$$\mathfrak{P}_{i,k+1|k+1} \leq X_{i,k+1|k+1}.$$

Finally, the specific expression of the estimator gain $K_{i,k+1}$ is given below. Setting

$$\begin{aligned} \Xi_{i,k+1} =\ & (1+\mu_3)\bar{\Phi}_{i,k+1}C_{i,k+1}X_{i,k+1|k}C_{i,k+1}^T\bar{\Phi}_{i,k+1}^T + (1+\mu_5^{-1})\mathfrak{R}_{i,k+1} + (1+\mu_3^{-1} \\ & +\mu_4+\mu_5)\pi_{i,k+1}I + (1+\mu_4^{-1})\Big[\Omega_{i,k+1} \circ (C_{i,k+1}\ddot{\Sigma}_{i,k+1}C_{i,k+1}^T)\Big] \end{aligned}$$

and completing the square regarding (11), then we can arrive at

$$\begin{aligned} X_{i,k+1|k+1} &= \Big[K_{i,k+1} - (1+\mu_3)X_{i,k+1|k}C_{i,k+1}^T\bar{\Phi}_{i,k+1}^T\Xi_{i,k+1}^{-1}\Big]\Xi_{i,k+1}\Big[K_{i,k+1} - (1+\mu_3) \\ &\quad \times X_{i,k+1|k}C_{i,k+1}^T\bar{\Phi}_{i,k+1}^T\Xi_{i,k+1}^{-1}\Big]^T + (1+\mu_3)X_{i,k+1|k} - (1+\mu_3)^2X_{i,k+1|k} \\ &\quad \times C_{i,k+1}^T\bar{\Phi}_{i,k+1}^T\Xi_{i,k+1}^{-1}\bar{\Phi}_{i,k+1}C_{i,k+1}X_{i,k+1|k}. \end{aligned}$$

There is no doubt that the form of $K_{i,k+1}$ in (12) can minimize $\mathrm{tr}(X_{i,k+1|k+1})$ and the proof is complete. □

Remark 3.6. It is worthwhile to point out that the constraint $\varepsilon_{i,k}^{-1}I - F_{i,k}X_{i,k|k}F_{i,k}^T > 0$ in Theorem 3.5 contains the positive parameter $\varepsilon_{i,k}$. During the algorithm implementation, the parameter $\varepsilon_{i,k}$ can be chose to ensure that the inequality constraint $\varepsilon_{i,k}^{-1}I - F_{i,k}X_{i,k|k}F_{i,k}^T > 0$ holds at each time step, which is displayed in the simulation section.

Summing up the above analysis, the following event-based estimation algorithm is presented.

Algorithm :
Step 1 : Set $k = 0$ and select other initial parameters.
Step 2 : Compute the prediction $\hat{x}_{i,k+1|k}$ via (4).
Step 3 : Calculate $X_{i,k+1|k}$ by (10).
Step 4 : Solve the estimator gain $K_{i,k+1}$ based on (12).
Step 5 : Compute the state estimation $\hat{x}_{i,k+1|k+1}$ by (5).
Step 6 : Calculate $X_{i,k+1|k+1}$ via (11).
Step 7 : Let $k = k+1$. Go to *Step* 2.

4. MONOTONICITY ANALYSIS

In this section, the estimation algorithm will be discussed, that is, the impact of fading probability onto the estimation algorithm performance is examined from the theoretical viewpoint. For the fading probability $\bar{\Phi}_{i,k+1} = \mathrm{diag}\{\bar{\phi}_{i,k+1}^1,\ \bar{\phi}_{i,k+1}^2,\ \cdots,\bar{\phi}_{i,k+1}^{n_2}\}$, let's assume that $\bar{\phi}_{i,k+1}^l = \bar{\phi}_{i,k+1}$ $(l = 1, 2, \cdots, n_2)$. In other words, $\bar{\Phi}_{i,k+1} = \bar{\phi}_{i,k+1}I$.

Theorem 4.1. If the fading probability $\bar{\phi}_{i,k+1}$ increases, it is not difficult to conclude that $\mathrm{tr}(X_{i,k+1|k+1})$ is non-increasing.

Proof. Taking the partial derivative of $\mathrm{tr}(X_{i,k+1|k+1})$ with respect to $\bar{\phi}_{i,k+1}$, we get

$$\begin{aligned} &\frac{\mathrm{dtr}(X_{i,k+1|k+1})}{\mathrm{d}\bar{\phi}_{i,k+1}} \\ =\ &\frac{\mathrm{dtr}}{\mathrm{d}\bar{\phi}_{i,k+1}}\Big[(1+\mu_3)X_{i,k+1|k} - (1+\mu_3)^2\bar{\phi}_{i,k+1}^2X_{i,k+1|k}C_{i,k+1}^T\Xi_{i,k+1}^{-1}C_{i,k+1}X_{i,k+1|k}\Big] \\ =\ &\mathrm{tr}\Big\{-2(1+\mu_3)^2\bar{\phi}_{i,k+1}X_{i,k+1|k}C_{i,k+1}^T\Xi_{i,k+1}^{-1}C_{i,k+1}X_{i,k+1|k} + (1+\mu_3)^2\bar{\phi}_{i,k+1}^2 \end{aligned}$$

$$
\begin{aligned}
&\quad \times X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} \big[2(1+\mu_3)\bar{\phi}_{i,k+1} C_{i,k+1} X_{i,k+1|k} C_{i,k+1}^T \big] \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} \Big\} \\
\leq &\quad \mathrm{tr}\Big\{ -2(1+\mu_3)^2 \bar{\phi}_{i,k+1} X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} + (1+\mu_3)^2 \bar{\phi}_{i,k+1} \\
&\quad \times X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} \big[2(1+\mu_3)\bar{\phi}_{i,k+1}^2 C_{i,k+1} X_{i,k+1|k} C_{i,k+1}^T + 2(1+\mu_5^{-1}) \mathfrak{R}_{i,k+1} \\
&\quad + 2(1+\mu_3^{-1}+\mu_4+\mu_5)\pi_{i,k+1} I + 2(1+\mu_4^{-1}) \Omega_{i,k+1} \circ (C_{i,k+1} \ddot{\Sigma}_{i,k+1} C_{i,k+1}^T) \big] \\
&\quad \times \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} \Big\} \\
= &\quad \mathrm{tr}\Big\{ -2(1+\mu_3)^2 \bar{\phi}_{i,k+1} X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} + 2(1+\mu_3)^2 \bar{\phi}_{i,k+1} \\
&\quad \times X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} \Big\} \\
= &\quad 0
\end{aligned}
$$

which indicates that this theorem holds and the proof is complete. □

Remark 4.2. So far, the Theorem 4.1 shows the relationship between $\mathrm{tr}(X_{i,k+1|k+1})$ and $\bar{\phi}_{i,k+1}$, which evaluates the performance of the developed estimation strategy. Obviously, the smaller value of $\bar{\phi}_{i,k+1}$ is, the greater possibility of data distortion occurs. During the proof of this theorem, note that $\vec{\phi}_{i,k+1}$ is irrelevant to $\bar{\phi}_{i,k+1}$. Generally, similar conclusion can be obtained regarding the correlation between $\vec{\phi}_{i,k+1}$ and $\bar{\phi}_{i,k+1}$ providing that the random variable $\Phi_{i,k+1}$ obeys the Bernoulli distribution with $\vec{\phi}_{i,k+1}^l = \bar{\phi}_{i,k+1}^l(1-\bar{\phi}_{i,k+1}^l)$. Then the corresponding proof in Theorem 4.1 can be rewritten as follows:

$$
\begin{aligned}
&\quad \frac{\mathrm{dtr}(X_{i,k+1|k+1})}{\mathrm{d}\bar{\phi}_{i,k+1}} \\
= &\quad \mathrm{tr}\Big\{ -2(1+\mu_3)^2 \bar{\phi}_{i,k+1} X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} + (1+\mu_3)^2 \bar{\phi}_{i,k+1}^2 \\
&\quad \times X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} \big[2(1+\mu_3)\bar{\phi}_{i,k+1} C_{i,k+1} X_{i,k+1|k} C_{i,k+1}^T + (1+\mu_4^{-1}) \\
&\quad \times (1-2\bar{\phi}_{i,k+1}) I \circ (C_{i,k+1} \ddot{\Sigma}_{i,k+1} C_{i,k+1}^T) \big] \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} \Big\} \\
\leq &\quad \mathrm{tr}\Big\{ -2(1+\mu_3)^2 \bar{\phi}_{i,k+1} X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} + (1+\mu_3)^2 \bar{\phi}_{i,k+1} \\
&\quad \times X_{i,k+1|k} C_{i,k+1}^T \Xi_{i,k+1}^{-1} \big[2\Xi_{i,k+1} - (1+\mu_4^{-1}) \bar{\phi}_{i,k+1} I \circ (C_{i,k+1} \ddot{\Sigma}_{i,k+1} C_{i,k+1}^T) \big] \\
&\quad \times \Xi_{i,k+1}^{-1} C_{i,k+1} X_{i,k+1|k} \Big\} \\
\leq &\quad 0.
\end{aligned}
$$

5. AN ILLUSTRATIVE EXAMPLE

In this section, a numerical simulation is employed to demonstrate the effectiveness of the proposed state estimation scheme based on the event-triggered protocol.

Consider the nonlinear time-varying dynamical networks (1) – (2) with the following parameters:

$$\begin{aligned}
&B_{1,k} = \begin{bmatrix} -1 & 1 \end{bmatrix}^T, \quad B_{2,k} = \begin{bmatrix} -1 - 0.1\sin(0.1k) & 2 \end{bmatrix}^T, \quad B_{3,k} = \begin{bmatrix} 2 & -2 \end{bmatrix}^T, \\
&C_{1,k} = \begin{bmatrix} -2 - 0.1\cos(0.6k) & 3 \end{bmatrix}, \quad C_{2,k} = \begin{bmatrix} -1 & 2 \end{bmatrix}, \quad C_{3,k} = \begin{bmatrix} -2 & 1 \end{bmatrix}, \\
&L_{1,k} = L_{2,k} = L_{3,k} = \mathrm{diag}\{0.2, \ 0.2\}, \quad F_{1,k} = F_{2,k} = F_{3,k} = \mathrm{diag}\{0.1, \ 0.1\}
\end{aligned}$$

and $x_{i,k} = [x^1_{i,k} \ \ x^2_{i,k}]^T$ is the state vector of the ith node and the estimation is $\hat{x}_{i,k|k} = [\hat{x}^1_{i,k|k} \ \ \hat{x}^2_{i,k|k}]^T$ $(i = 1, 2, 3)$. The initial values of this paper are $x_{1,0} = [-0.3 \ \ 0.2]^T$, $x_{2,0} = [0.1 \ \ 0.4]^T$, $x_{3,0} = [0.1 \ \ 0.4]^T$, $X_{1,0|0} = X_{2,0|0} = X_{3,0|0} = 2I_2$. Other parameters are set as $\mu_1 = 0.05$, $\mu_2 = 0.1$, $\mu_3 = 2$, $\mu_4 = 1$, $\mu_5 = 1$, $\mu_6 = 0.15$, $\mathfrak{Q}_{i,k} = 0.5$, $\mathfrak{R}_{1,k} = 0.02$, $\mathfrak{R}_{2,k} = \mathfrak{R}_{3,k} = 0.01$, $\bar{\Phi}_{i,k} = 0.5$, $\vec{\Phi}_{i,k} = 0.1$, $\hat{x}_{i,0|0} = x_{i,0} - [1 \ \ 1]^T$, $\varepsilon_{i,k} = [1.1\lambda_{\max}(F_{i,k}X_{i,k|k}F^T_{i,k}) + 0.1]^{-1}$. Select the coupling configuration matrix $\Gamma = \mathrm{diag}\{0.2, \ 0.2\}$ and $W = [\omega_{ij}]_{3\times 3}$ with $\omega_{ij} = -0.2 \ \ (i = j)$ and $\omega_{ij} = 0.1 \ \ (i \neq j)$. $\Delta\omega_{ij}$ is a random number in the interval $[-0.1, 0.1]$ and $\delta_{ij} = 0.1$. The nonlinear function has the following form

$$f(x_{i,k}) = \begin{bmatrix} -0.1x^1_{i,k} + 0.3x^2_{i,k} - 0.05\sin(x^1_{i,k}x^2_{i,k}) \\ -0.2x^1_{i,k} - 0.1x^2_{i,k} + 0.06\cos(x^1_{i,k}x^2_{i,k}) \end{bmatrix}.$$

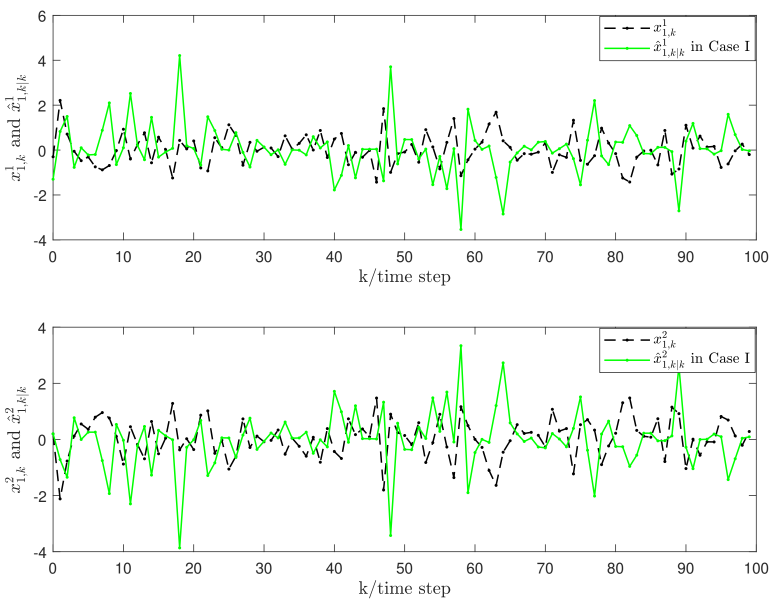

Fig. 1. The real state $x_{1,k}$ and the estimation $\hat{x}_{1,k|k}$ in Case I.

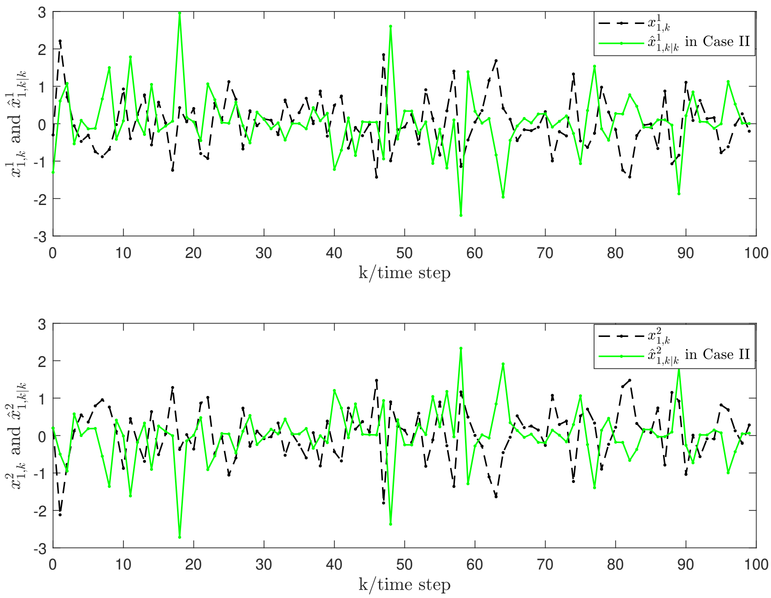

Fig. 2. The real state $x_{1,k}$ and the estimation $\hat{x}_{1,k|k}$ in Case II.

Based on Theorem 3.5, the addressed optimized state estimation problem can be solved and the desirable estimation scheme can be obtained, where the corresponding results are showed in Figures 1−8. From Figures 1−6, we can see that the developed estimation algorithm performs a good performance to track the real states of network nodes under Case I ($\bar{\Phi}_{i,k} = 0.5$) and Case II ($\bar{\Phi}_{i,k} = 0.85$). According to Figure 7, we can conclude that the log(MSE) (mean square error) of state $x_{i,k}$ is always below the trace of obtained upper bound. Figure 8 plots the $\mathrm{tr}(X_{i,k|k})$ with respect to different fading probabilities, which further shows the relationship mentioned in the Theorem 4.1, i. e., the measurements undergo less fading or missing impacts, and the trace of the upper bound of the estimation error covariance is more smaller. This observation is clearly shown from theoretical and experimental aspects.

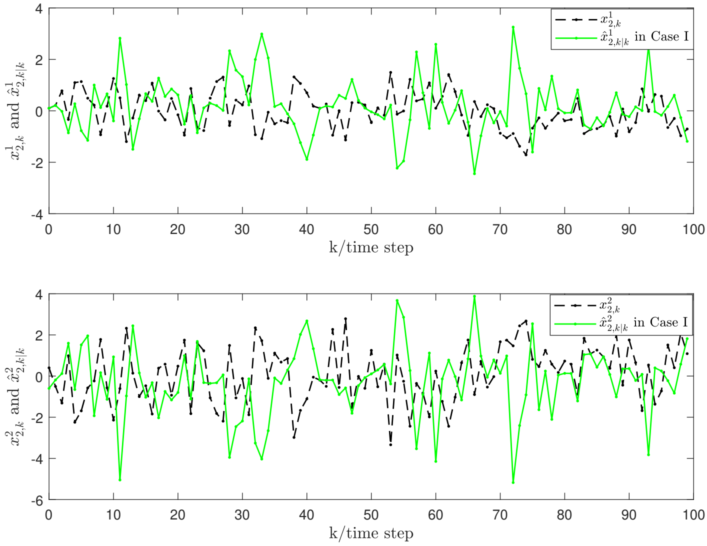

Fig. 3. The real state $x_{2,k}$ and the estimation $\hat{x}_{2,k|k}$ in Case I.

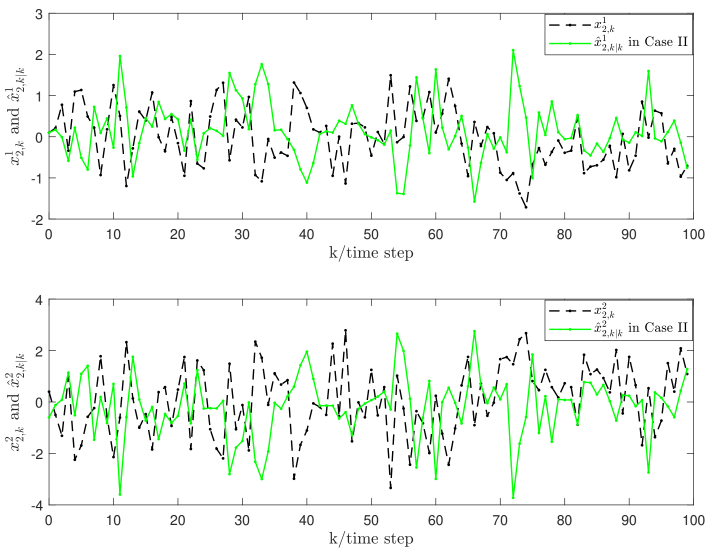

Fig. 4. The real state $x_{2,k}$ and the estimation $\hat{x}_{2,k|k}$ in Case II.

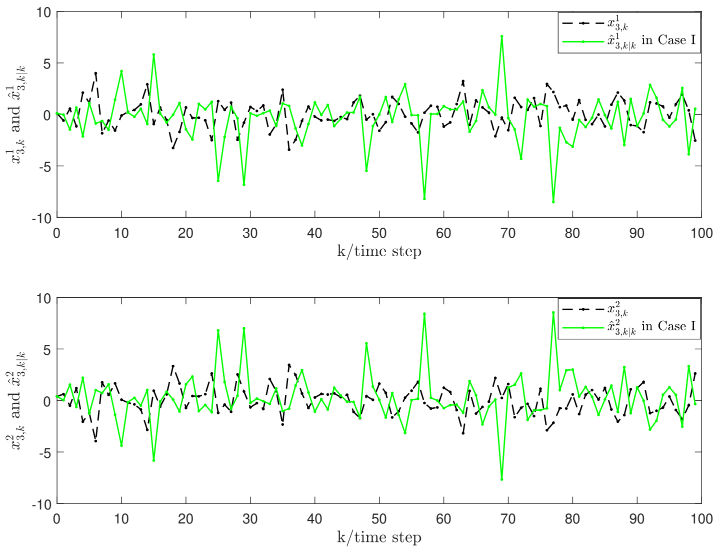

Fig. 5. The real state $x_{3,k}$ and the estimation $\hat{x}_{3,k|k}$ in Case I.

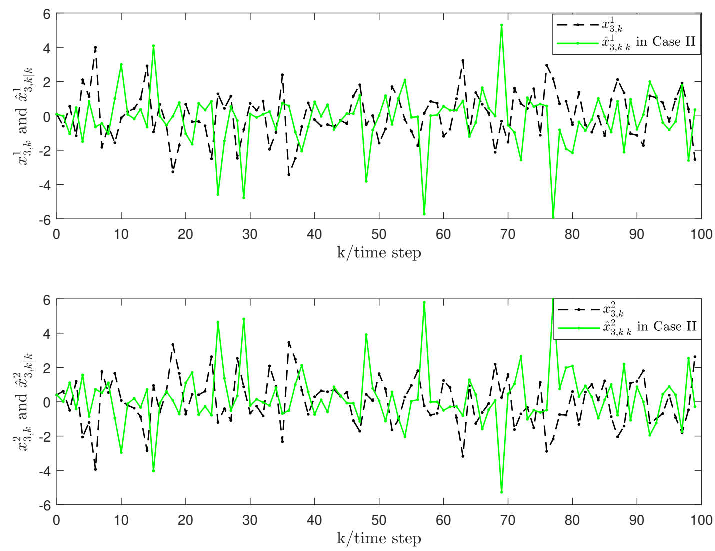

Fig. 6. The real state $x_{3,k}$ and the estimation $\hat{x}_{3,k|k}$ in Case II.

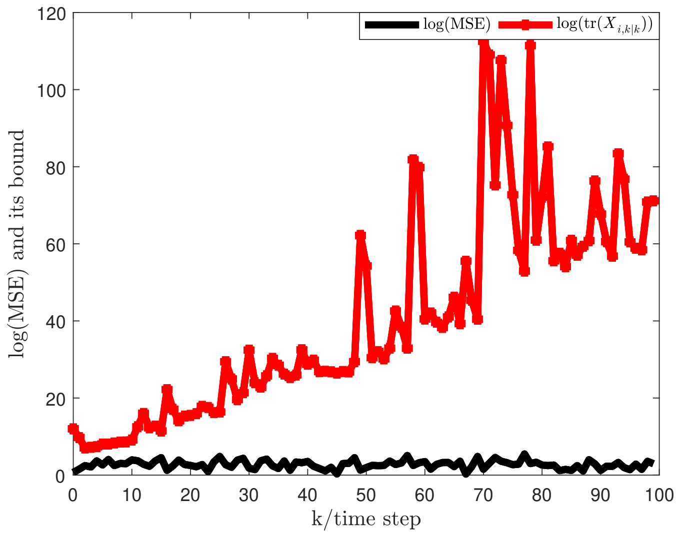

Fig. 7. log(MSE) and log(tr($X_{i,k|k}$)).

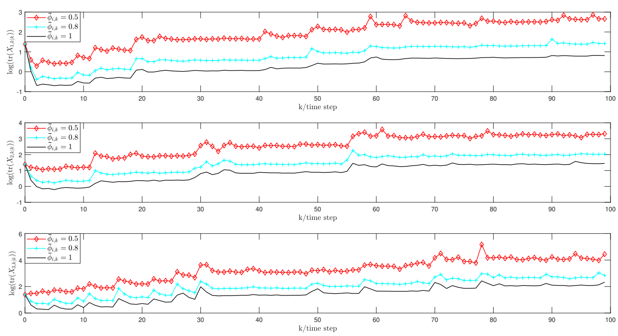

Fig. 8. log(tr($X_{i,k|k}$)) regarding different fading probabilities.

6. CONCLUSIONS

In this paper, we have concerned with the optimized state estimation problem for a class of nonlinear time-varying complex networks with event-based communication protocol, fading measurements and stochastic coupling strength. A minimized upper bound of estimation error covariance has been obtained via designing the estimator in an acceptable way. Moreover, the fact that the trace of the minimum upper bound is always non-increasing when the fading probability increases has been revealed. Finally, a numerical simulation has been given to illustrate the validity of the presented state estimation strategy. Further topics include the extensions on the state estimation problems for time-varying dynamical networks with different communication protocols (e. g. Round–Robin protocol, stochastic communication protocol) with hope to further regulate the communication transmissions, where new technique should be introduced to deal with the effects caused by those protocols. Besides, the saturation phenomenon is commonly occurred as mentioned in [4, 5], there is also interesting to address the problems of state estimation and algorithm performance analysis for saturated complex networks based on the proposed method.

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