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Recursive Resilient State Estimation for Nonlinear Stochastic Complex Networks With Energy Harvesting Sensors Under Deception Attacks

Yu-Ang Wang, Zidong Wang, Lei Zou, and Fan Wang

***Abstract*—This paper deals with a resilient estimation problem for certain type of time-varying complex networks of energy harvesting sensors that are vulnerable to deception attacks. Measurement signals of the underlying complex network, as measured by energy harvesting sensors, are only given to a remote estimator when the energy level is adequate to offset the energy consumption, which is at risk of deception attacks during network transmission. The deception attacks under consideration, are depicted as events occurring randomly, governed by a Bernoulli sequence. To meet the desired estimation performance, a resilient scheme is developed that addresses the side effects of random perturbations of the estimator gain when it comes to the implementation. The primary objective is to devise a resilient algorithm that can simultaneously manage energy harvesting sensors, deception attacks, and gain perturbations of the state estimator. Initially, the upper bound of the obtained error covariance is determined by making use of induction and intensive stochastic techniques. The necessary estimator gains are then identified recursively to prudently minimize this acquired bound. An illustrative example is presented ultimately to demonstrate this scheme's efficacy.**

***Index Terms*—Complex networks, energy harvesting sensors, resilient estimation, deception attacks, nonlinear systems.**

I. Introduction

Complex networks (CNs) are distinguished by their dynamic behaviors, unique topological characteristics, and robust modeling capabilities for complex systems with web-like structures. In recent years, extensive studies have been conducted on CNs, encompassing various domains such as the stock market [1], social dilemmas [2], and disease spreading [3], among others. Significant research has been directed towards the performance of nodes' interconnections in CNs, with particular focus on the transmission strategy [4] and link prediction [5]. The dynamics of nodes within CNs have emerged as a critical area drawing increased research interest, which has led to investigations into synchronization problems [6], pinning control problems [7], [8], and state estimation problems [9], [10].

In system science, state estimation has been identified as a fundamental issue and has undergone extensive exploration due to its broad applicability in areas such as navigation and radar tracking systems [11]. A significant percentage of research has been conducted about various aspects of state estimation [12]–[17]. Among the developed methods, the Kalman filtering scheme, which seeks to minimize the estimation error covariance (EEC), is recognized as the optimal approach for linear systems affected by Gaussian noises [18]–[20]. However, for nonlinear systems, traditional Kalman filtering is no longer applicable [21]. Consequently, the development of suitable estimation methods capable of addressing nonlinearities has become important, both in theoretical and practical contexts.

For state estimation problems, it is commonly assumed in most existing literature that the estimator gain is implemented exactly without any perturbation during the algorithm implementation. However, this assumption does not align with many real-world scenarios. In practical engineering, there is a likelihood of non-zero fluctuations in the gain of the designed estimator due to physical constraints such as component aging and finite word length. Note that the estimation performance is highly sensitive to such perturbations, and even minor variations in the gain of the estimator are known to deteriorate the estimation performance. Thus, it is very necessary to design one effective scheme to maintain estimation performance in presence of perturbations into estimator gains, and this necessity has given rise to what is commonly referred to as the *resilient* state estimation problem [22]–[27].

Energy limitation is a critical issue in wireless communication systems. Energy harvesting sensors (EHSs), as a type of energy replenishment scheme, are extensively utilized in systems to prevent energy depletion in communication equipment. Typically, the harvesting technology involves using an energy harvester, such as a windmill, solar panel, or other devices, to extract energy from the outside environment as well as store the converted power of sensors for communication purposes. A significant challenge in the study of EHSs is managing the special sensing logic when designing the estimator. Energy harvesting can introduce measurement losses which, if not properly addressed, could significantly impair system performance. To tackle this issue, various research efforts have been directed towards filtering problems associated with EHSs,

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see e.g. [28]–[33].

Cybersecurity of communication networks recently has consistently been a focal area within the fields of communication technology and signal processing. The development of wireless communication technology has facilitated network-based communication offering notable advantages. However, the adoption of wireless communication networks also presents additional challenges. For instance, data in most networked industrial systems, such as electric power systems and petrochemical engineering, is susceptible to cyber-attacks during transmission over wireless networks if effective data protection measures are not in place. As a result, state estimation problems have recently garnered particular interest in networked systems prone to cyber-attacks, see e.g. [34]–[37].

Cyber-attacks, as factors that significantly impair system performance, are frequently utilized by adversaries to disrupt the normal data flow within communication networks. In engineering, the commonly encountered attacks include attacks of false data injection [38]–[41], deception [42], denial-of-service [43], [44], and replay [45]. Among these, deception attacks aim to destabilize or deteriorate the target system by injecting malicious data. Also, it has been demonstrated that traditional false data detection schemes are ineffective in detecting deception attacks [46]–[48]. Consequently, numerous efforts have been directed towards investigating secure control and filtering topics under the influence of deception attacks [49]–[52]. Despite these efforts, nonlinear resilient estimation for CNs, particularly in the presence of deception attacks and EHSs, has not fully been explored.

As previously noted, designing resilient state estimators for CNs under the combined effects of EHSs and deception attacks holds practical significance. This study faces several substantial challenges. The first challenge is the design of a resilient estimator that minimizes the upper bound of the EEC while contending with EHSs and deception attacks. Furthermore, the handling of measurement outputs generated by EHSs, particularly when sensor energy storage is depleted, presents a significant challenge since improper handling could severely impact estimation performance. Therefore, the second difficulty involves analyzing the transient behavior of state estimation errors resulting from the use of energy stored in the sensors. Moreover, in the context of cyber-attacks, it is crucial to recognize that not all attempts by an adversary may be successful, and the success ratio of attacks plays a critical role in affecting estimation performance. Thus, the third challenge is to develop an attack model that accurately captures probabilistic nature of successful attacks, and to effectively utilize this success rate in implementing the proposed estimator. Accordingly, this research devises effective strategies to address these identified challenges.

Motivated by the discussions made thus far, our research is dedicated to addressing the challenges of designing a robust estimator that can effectively manage the complexities introduced by deception attacks and EHSs through the development of a recursive estimation algorithm. The following major contributions of this study are emphasized to underline its novelty and technical advancements.

1) The problem of resilient estimation is firstly and systematically studied for CNs that are equipped with EHSs and are vulnerable to deception attacks.

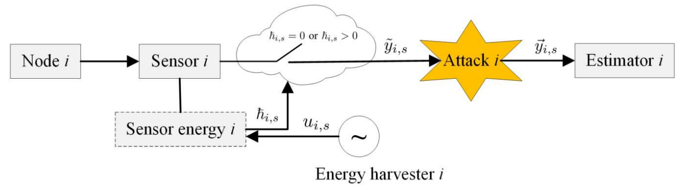

Fig. 1. State estimation with EHSs and deception attacks.

2) The EEC upper bound is calculated through a novel approach involving the recursive solution of two Riccati-like difference equations. This method provides a systematic and efficient means to handle the uncertainties and dynamics introduced by EHSs and cyber threats.
3) The estimator gains, critical for achieving desired estimation accuracy, are derived using a recursive calculation method, which ensures that the gains are adjusted dynamically in response to changes in system conditions and attack dynamics, thereby enhancing estimator resilience and reliability.

Section II introduces basic concepts and outlines the system configuration, including the model, the mechanics of the EHSs, the nature of deception attacks, and estimator resilience. In Section III, we derive the EEC bound and detail the recursive gain calculation. Section IV demonstrates this scheme's efficacy. Section V summarizes main findings and suggesting future research directions.

II. PROBLEM FORMULATION

A. System Model

System construction is illustrated in Fig. 1, which highlights how the openness and shared nature of communication networks make systems susceptible to cyber-attacks. This subsection initially develops a system model without cyber-attacks, which we will subsequently extend to include attack scenarios in Subsection II-C.

Consider a CN with N nodes and EHSs depicted in Fig. 1, where the EHSs are designed to collect possible energy from the environment and store it in rechargeable batteries. These sensors have the capability to transmit measurements to a remote estimator for processing estimation tasks. The plant dynamics and the corresponding measurements are

$$\begin{cases} x_{i,s+1} = f(x_{i,s}) + \sum_{j=1}^{N} \theta_{ij} \Gamma x_{j,s} + B_{i,s}\omega_{i,s} \\ y_{i,s} = C_{i,s}x_{i,s} + D_{i,s}\nu_{i,s} \end{cases} \tag{1}$$

where, for node i ($i \in \mathcal{E} \triangleq \{1, 2, \ldots, N\}$), $x_{i,s} \in \mathbb{R}^{n_x}$ denotes the internal state variable and $y_{i,s} \in \mathbb{R}^{n_y}$ refers to the measurement output. Mutually uncorrelated and zero-mean $\nu_{i,s} \in \mathbb{R}^{n_\nu}$ and $\omega_{i,s} \in \mathbb{R}^{n_\omega}$ stand for, respectively, the measurement and the process noises with $\mathbb{E}\{\omega_{i,s}\omega_{i,s}^T\} = W_{i,s}$ and $\mathbb{E}\{\nu_{i,s}\nu_{i,s}^T\} = V_{i,s}$. $x_{i,0}$ with a known mean is independent of $\nu_{i,s} \in \mathbb{R}^{n_\nu}$ and $\omega_{i,s} \in \mathbb{R}^{n_\omega}$. Γ is an inner coupling matrix

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and is given. $\Theta = (\theta_{ij}) \in \mathbb{R}^{N\times N}$ is a coupled network configuration matrix with $\theta_{ij} \geq 0$ $(i \neq j)$ (not all zeros). Matrices $B_{i,s}$, $C_{i,s}$ and $D_{i,s}$ are known.

The nonlinear function $f(\cdot) : \mathbb{R}^{n_x} \to \mathbb{R}^{n_x}$ satisfies [54]:

$$\begin{aligned} f(0) =&0, \\ \|f(z_1) - f(z_2)\| \leq&\alpha\|z_1 - z_2\| \end{aligned} \tag{2}$$

where z_1 and $z_2 \in \mathbb{R}^{n_x}$ are two arbitrarily given vectors, and scalar $\alpha > 0$ is known.

B. Energy Harvesting Model

Energy supply is a critical procedure in controlling and monitoring systems, given that information transmission consumes significant energy. Therefore, implementing efficient energy replenishment strategies to maintain normal operation of an entire network is crucial for energy harvesting and storage.

In this scenario, the transmission of measurement outputs is contingent upon energy stored. For node i, the maximum capacity to store energy is denoted by Φ_i. Once node i reaches its capacity limit, it is unable to store any additional energy harvested from its surroundings until some of the stored energy is consumed. The energy harvested at time s by sensor i is $u_{i,s}$, and $u_{i,s}$ is assumed to be identically and also independently distributed (i.i.d.) random variables satisfying

$$\mathrm{Prob}\{u_{i,s} = \pi\} = g_\pi, \quad \pi = 0, 1, 2\cdots \tag{3}$$

where g_π is a known scalar satisfying $\sum_{\pi=0}^{+\infty} g_\pi = 1$ and $0 \leq g_\pi \leq 1$.

At the time s, for node i of energy level $\hbar_{i,s} \in \{0, 1, 2, \cdots, \Phi_i\}$, if there is stored energy in node i, the measurement signal is transmitted normally by consuming one unit of energy. Conversely, if the energy stored is insufficient, the measured signal cannot be transmitted and no energy is consumed. In this scenario, any measurement signal that fails to be transmitted due to the lack of energy is discarded [32]. As such, the dynamics of $\hbar_{i,s}$ with the initial condition $\hbar_{i,0} \leq \Phi_i$ can be expressed by

$$\hbar_{i,s+1} = \min\{\hbar_{i,s} + u_{i,s} - \Upsilon_{i,\hbar_{i,s}}, \Phi_i\} \tag{4}$$

where

$$\Upsilon_{i,\hbar_{i,s}} \triangleq \begin{cases} 1, & \hbar_{i,s} > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Based on the previous discussions, the information collected by the estimator from sensor i can be modeled as follows:

$$\tilde{y}_{i,s} = \Upsilon_{i,\hbar_{i,s}} y_{i,s}, \quad i \in \mathcal{E}. \tag{6}$$

C. Deception Attacks

Generally, success of attacks implemented by an attacker depends on both network condition and device performance. Therefore, for node i, attacks can be mathematically considered as a randomly occurring event, and attacked signals during transmissions are modeled as follows:

$$\begin{cases} \vec{y}_{i,s} =\tilde{y}_{i,s} + \varphi_{i,s}\eta_{i,s} \\ \eta_{i,s} =-\tilde{y}_{i,s} + \xi_{i,s} \end{cases} \tag{7}$$

where $\vec{y}_{i,s} \in \mathbb{R}^{n_y}$ $(i \in \mathcal{E})$ represents the received signal of i-th estimator subject to random attacks, $\eta_{i,s} \in \mathbb{R}^{n_y}$ is a nonzero signal injected by adversaries, and $\xi_{i,s} \in \mathbb{R}^{n_y}$ satisfies

$$\|\xi_{i,s}\| \leq \bar{\xi}_i \tag{8}$$

with $\bar{\xi}_i$ being a known positive scalar. The random variables $\varphi_{i,s}$ $(i \in \mathcal{E})$ are white sequences of the Bernoulli distribution with probabilities of values 0 or 1 as follows:

$$\begin{aligned} \mathrm{Prob}\{\varphi_{i,s} = 0\} =&1 - \bar{\varphi}_i, \\ \mathrm{Prob}\{\varphi_{i,s} = 1\} =&\bar{\varphi}_i \end{aligned}$$

with $\bar{\varphi}_i \in [0, 1)$ is known.

Remark 1: Due to the implementation of security protection devices and the presence of CN fluctuations, an attacker might not always be able to infect the estimator with the attack signal at a specific time. Consequently, a set of stochastic variable sequences that obey Bernoulli distributions is introduced to characterize ratios of successful attacks, thereby reflecting attack behavior.

D. Resilient State Estimator

For CN (1) with measurements signals modeled by (7), we adopt a resilient state estimator for node i of the following structure:

$$\begin{cases} \hat{x}_{i,s+1|s} =f(\hat{x}_{i,s|s}) + \sum_{j=1}^{N} \theta_{ij}\Gamma\hat{x}_{j,s|s} \\ \hat{x}_{i,s+1|s+1} =\hat{x}_{i,s+1|s} + (K_{i,s+1} + \Delta_{i,s+1})\big(\vec{y}_{i,s+1} \\ \qquad\qquad - (1 - \bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\big) \end{cases} \tag{9}$$

where $\psi_{i,s} \triangleq \mathbb{E}\{\Upsilon_{i,\hbar_{i,s}}\}$, $\hat{x}_{i,s+1|s} \in \mathbb{R}^{n_x}$ is the one-step prediction of $x_{i,s+1}$, $\hat{x}_{i,s+1|s+1} \in \mathbb{R}^{n_x}$ is the state estimate of $x_{i,s+1}$, $K_{i,s+1} \in \mathbb{R}^{n_x\times n_y}$ is the estimator parameter, and $\Delta_{i,s+1} \in \mathbb{R}^{n_x\times n_y}$ denotes gain fluctuations satisfying:

$$\begin{aligned} \mathbb{E}\{\Delta_{i,s+1}\} =&0 \\ \mathbb{E}\{\Delta_{i,s+1}\Delta_{i,s+1}^T\} \leq&\gamma_i I \end{aligned} \tag{10}$$

with γ_i being a known scalar.

Remark 2: The perturbed matrix $\Delta_{i,s+1}$ reflects the error induced possibly by fixed length of words of given computation software and limited resolution of equipment. One goal here is to address the above unknown matrix by enhancing the resilience of the proposed algorithm against parameter perturbation.

For the i-th node, we denote $e_{i,s+1|s} \triangleq x_{i,s+1} - \hat{x}_{i,s+1|s}$ and $e_{i,s+1|s+1} \triangleq x_{i,s+1} - \hat{x}_{i,s+1|s+1}$ as one-step prediction and estimation errors, respectively. Furthermore, we denote covariances $P_{i,s+1|s} \triangleq \mathbb{E}\{e_{i,s+1|s}e_{i,s+1|s}^T\}$ and $P_{i,s+1|s+1} \triangleq \mathbb{E}\{e_{i,s+1|s+1}e_{i,s+1|s+1}^T\}$.

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According to (1) and (9), we have

$$\begin{cases} e_{i,s+1|s} = \tilde{f}(e_{i,s|s}) + B_{i,s}\omega_{i,s} + \sum_{j=1}^{N}\theta_{ij}\Gamma e_{j,s|s} \\ e_{i,s+1|s+1} = \big(I - (1-\bar{\varphi}_i)\psi_{i,s+1}\bar{K}_{i,s+1}C_{i,s+1}\big)e_{i,s+1|s} \\ \quad - \bar{K}_{i,s+1}\big((1-\varphi_{i,s+1})\Upsilon_{i,\hbar_{i,s}} \\ \quad - (1-\bar{\varphi}_i)\psi_{i,s+1}\big)C_{i,s+1}x_{i,s+1} \\ \quad - \bar{K}_{i,s+1}(1-\varphi_{i,s+1})\Upsilon_{i,\hbar_{i,s}}D_{i,s+1}\nu_{i,s+1} \\ \quad - \bar{K}_{i,s+1}\varphi_{i,s+1}\xi_{i,s+1} \end{cases} \tag{11}$$

where

$$\tilde{f}(e_{i,s|s}) \triangleq f(x_{i,s}) - f(\hat{x}_{i,s|s}),$$
$$\bar{K}_{i,s+1} \triangleq K_{i,s+1} + \Delta_{i,s+1}.$$

Remark 3: In this proposed resilient estimator, each node utilizes only local and available information to estimate the state. The interconnections among nodes, compounded by estimator parameter perturbations, make it challenging to compute the accurate EEC $P_{i,s+1|s+1}$. Therefore, our focus is on developing a method that calculates the upper EEC bound and minimizes it.

The objective is to design resilient state estimator (9) for system (1) in order to

1) establish bounds $\bar{\Re}_{i,s+1|s}$ and $\bar{\Re}_{i,s+1|s+1}$ for EECs such that
$$P_{i,s+1|s} \le \bar{\Re}_{i,s+1|s}$$
$$P_{i,s+1|s+1} \le \bar{\Re}_{i,s+1|s+1},$$
2) recursively calculate the desired estimator gains $K_{i,s+1}$ by minimizing $\bar{\Re}_{i,s+1|s+1}$.

III. Main Results

The following lemmas serve as the theoretical basis for deriving the main results.

Lemma 1: [53] Let matrices L, N, K and H be given. We have the following relationships:

$$\frac{\partial \mathrm{tr}(LKN)}{\partial K} = L^T N^T, \quad \frac{\partial \mathrm{tr}(LK^T N)}{\partial K} = NL,$$
$$\frac{\partial \mathrm{tr}((LKN)H(LKN)^T)}{\partial K} = 2L^T LKNHN^T. \tag{12}$$

Lemma 2: [54] For a positive scalar β and any given vectors μ and ϱ, the following inequality holds:

$$\mu\varrho^T + \varrho\mu^T \le \beta\mu\mu^T + \beta^{-1}\varrho\varrho^T. \tag{13}$$

Lemma 3: [32] Let $\{\hbar_{i,s}\}_{s\ge 0}$ be the energy level with distribution (4). Denote $\chi_{i,s} \triangleq \big[\mathrm{Prob}\{\hbar_{i,s}=0\} \;\; \mathrm{Prob}\{\hbar_{i,s}=1\} \;\; \cdots \;\; \mathrm{Prob}\{\hbar_{i,s}=\Phi_i\}\big]^T$. Then, recursion of $\chi_{i,s}$ is

$$\chi_{i,s+1} = \varepsilon_i + \Xi_i\chi_{i,s} \tag{14}$$

whose initial condition is given by

$$\chi_{i,0} = [\underbrace{0 \;\; \cdots \;\; 0}_{\hbar_{i,0}} \;\; 1 \;\; \underbrace{0 \;\; \cdots \;\; 0}_{\Phi_i - \hbar_{i,0}}]^T$$

where

$$\varepsilon_i \triangleq \big[\underbrace{0 \;\; \cdots \;\; 0}_{\Phi_i} \;\; 1\big]^T,$$

$$\Xi_i \triangleq -\begin{bmatrix} -g_0 & -g_0 & 0 & \cdots & 0 \\ -g_1 & -g_1 & -g_0 & \cdots & 0 \\ -g_2 & -g_2 & -g_1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -g_{\Phi_i-1} & -g_{\Phi_i-1} & -g_{\Phi_i-2} & \cdots & -g_0 \\ \sum_{\pi=0}^{\Phi_i-1} g_\pi & \sum_{\pi=0}^{\Phi_i-1} g_\pi & \sum_{\pi=0}^{\Phi_i-2} g_\pi & \cdots & g_0 \end{bmatrix}.$$

From Lemma 3, it is easy to observe that

$$\psi_{i,s} = \mathrm{Prob}\{\Upsilon_{i,\hbar_{i,s}} = 1\} = [0 \;\; \underbrace{1 \;\; \cdots \;\; 1}_{\Phi_i}]\chi_{i,s}. \tag{15}$$

In the following theorem, we construct certain upper bounds for the error covariances.

Theorem 1: Let β_1, β_2, β_3 and $\tilde{\beta}$ be given positive scalars. Given two sequences of matrices $\{\bar{\Re}_{i,s+1|s}\}_{s\ge 0}$ and $\{\bar{\Re}_{i,s+1|s+1}\}_{s\ge 0}$ with $\bar{\Re}_{i,0|0} = P_{i,0|0}$ satisfying the following difference equations:

$$\begin{aligned} &\bar{\Re}_{i,s+1|s} \\ =&(1+\beta_1)\bar{\theta}_i\sum_{j=1}^{N}\theta_{ij}\Gamma\bar{\Re}_{j,s|s}\Gamma^T + B_{i,s}W_{i,s}B_{i,s}^T \\ &+ \alpha^2(1+\beta_1^{-1})\mathrm{tr}\{\bar{\Re}_{i,s|s}\}I, \end{aligned} \tag{16}$$

$$\begin{aligned} &\bar{\Re}_{i,s+1|s+1} \\ =&(1+\beta_2)P_{i,s+1|s} - (1+\beta_2)\tau_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T K_{i,s+1}^T \\ &- (1+\beta_2)\tau_{i,s+1}K_{i,s+1}C_{i,s+1}\bar{\Re}_{i,s+1|s} \\ &+ (\sigma_{i,s+1}+\phi_{i,s+1})K_{i,s+1}C_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T K_{i,s+1}^T \\ &+ (\sigma_{i,s+1}+\phi_{i,s+1})\lambda_{\max}(C_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T)\gamma_i I \\ &+ \phi_{i,s+1}K_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^T C_{i,s+1}^T K_{i,s+1}^T \\ &+ \phi_{i,s+1}\lambda_{\max}(C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^T C_{i,s+1}^T)\gamma_i I \\ &+ \tau_{i,s+1}K_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^T K_{i,s+1}^T \\ &+ \tau_{i,s+1}\lambda_{\max}(D_{i,s+1}V_{i,s+1}D_{i,s+1}^T)\gamma_i I \\ &+ (1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i K_{i,s+1}K_{i,s+1}^T\bar{\xi}_i^2 I \\ &+ (1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\bar{\xi}_i^2\gamma_i I \end{aligned} \tag{17}$$

where

$$\begin{aligned} \rho_{i,s+1} &\triangleq (1-\bar{\varphi}_i)\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}], \\ \phi_{i,s+1} &\triangleq (1+\beta_2)(1+\tilde{\beta})\rho_{i,s+1}, \\ \tau_{i,s+1} &\triangleq (1-\bar{\varphi}_i)\psi_{i,s+1}, \\ \sigma_{i,s+1} &\triangleq (1+\beta_2)\tau_{i,s+1}^2, \end{aligned} \tag{18}$$

then, the solution of (17) is proven to be an upper bound of $P_{i,s+1|s+1}$.

Proof: According to the definition of $P_{i,s+1|s}$ and (11), we have

$$\begin{aligned} &P_{i,s+1|s} \\ =&\mathbb{E}\{e_{i,s+1|s}e_{i,s+1|s}^T\} \\ =&\sum_{j=1}^{N}\sum_{p=1}^{N}\theta_{ij}\theta_{ip}\mathbb{E}\{\Gamma e_{j,s|s}e_{p,s|s}^T\Gamma^T\} \end{aligned}$$

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$$
\begin{aligned}
&+\mathbb{E}\{f(e_{i,s|s})f^T(e_{i,s|s})\}+B_{i,s}W_{i,s}B_{i,s}^T\\
&+\sum_{j=1}^{N}\theta_{ij}\mathbb{E}\{\Gamma e_{j,s|s}f^T(e_{i,s|s})\}\\
&+\sum_{j=1}^{N}\theta_{ij}\mathbb{E}\{f(e_{i,s|s})e_{j,s|s}^T\Gamma^T\}.
\end{aligned}\tag{19}
$$

Notice that the term $\sum_{j=1}^{N}\sum_{p=1}^{N}\theta_{ij}\theta_{ip}\mathbb{E}\{\Gamma e_{j,s|s}e_{p,s|s}^T\Gamma^T\}$ can be calculated as follows:

$$
\begin{aligned}
&\sum_{j=1}^{N}\sum_{p=1}^{N}\theta_{ij}\theta_{ip}\mathbb{E}\{\Gamma e_{j,s|s}e_{p,s|s}^T\Gamma^T\}\\
=&\frac{1}{2}\sum_{j=1}^{N}\sum_{p=1}^{N}\theta_{ij}\theta_{ip}\mathbb{E}\{\Gamma e_{j,s|s}e_{p,s|s}^T\Gamma^T+\Gamma e_{p,s|s}e_{j,s|s}^T\Gamma^T\}\\
\le&\frac{1}{2}\sum_{j=1}^{N}\sum_{p=1}^{N}\theta_{ij}\theta_{ip}(\Gamma P_{j,s|s}\Gamma^T+\Gamma P_{p,s|s}\Gamma^T)\\
=&\bar{\theta}_i\sum_{j=1}^{N}\theta_{ij}\Gamma P_{j,s|s}\Gamma^T
\end{aligned}\tag{20}
$$

where $\bar{\theta}_i=\sum_{p=1}^{N}\theta_{ip}$. Then, by using Lemma 2, we obtain

$$
\begin{aligned}
&\sum_{j=1}^{N}\theta_{ij}\mathbb{E}\{\Gamma e_{j,s|s}f^T(e_{i,s|s})\}+\sum_{j=1}^{N}\theta_{ij}\mathbb{E}\{f(e_{i,s|s})e_{j,s|s}^T\Gamma^T\}\\
&\le\beta_1\bar{\theta}_i\sum_{j=1}^{N}\theta_{ij}\Gamma P_{j,s|s}\Gamma^T+\beta_1^{-1}\mathbb{E}\{f(e_{i,s|s})f^T(e_{i,s|s})\}.
\end{aligned}\tag{21}
$$

In addition, with the aid of (2), one has that

$$
\begin{aligned}
&\mathbb{E}\{f(e_{i,s|s})f^T(e_{i,s|s})\}\\
\le&\mathbb{E}\{f^T(e_{i,s|s})f(e_{i,s|s})I\}\\
\le&\alpha^2\mathbb{E}\{e_{i,s|s}^Te_{i,s|s}I\}\le\alpha^2\mathrm{tr}\{P_{i,s|s}\}I.
\end{aligned}\tag{22}
$$

Substituting (20), (21) and (22) into (19) yields

$$
\begin{aligned}
P_{i,s+1|s}\le&(1+\beta_1)\bar{\theta}_i\sum_{j=1}^{N}\theta_{ij}\Gamma P_{j,s|s}\Gamma^T+B_{i,s}W_{i,s}B_{i,s}^T\\
&+\alpha^2(1+\beta_1^{-1})\mathrm{tr}\{P_{i,s|s}\}I.
\end{aligned}\tag{23}
$$

It follows from (11) and $P_{i,s+1|s+1}$'s definition that

$$
\begin{aligned}
&P_{i,s+1|s+1}\\
=&\mathbb{E}\{e_{i,s+1|s+1}e_{i,s+1|s+1}^T\}\\
=&\mathbb{E}\big\{(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})e_{i,s+1|s}e_{i,s+1|s}^T\\
&\times(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})^T\big\}+\mathbb{E}\big\{[(1-\varphi_{i,s+1})\\
&\times\Upsilon_{i,s+1}-(1-\bar{\varphi}_i)\psi_{i,s+1}]^2\bar{K}_{i,s+1}C_{i,s+1}x_{i,s+1}x_{i,s+1}^T\\
&\times C_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}+\mathbb{E}\big\{[(1-\varphi_{i,s+1})\Upsilon_{i,s+1}]^2\bar{K}_{i,s+1}\\
&\times D_{i,s+1}\nu_{i,s+1}\nu_{i,s+1}^TD_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}\\
&+\mathbb{E}\big\{\varphi_{i,s+1}^2\bar{K}_{i,s+1}\xi_{i,s+1}\xi_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}\\
&-L_1-L_1^T+L_2+L_2^T
\end{aligned}\tag{24}
$$

where

$$
\begin{aligned}
L_1\triangleq&\mathbb{E}\big\{(I-\bar{K}_{i,s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})e_{i,s+1|s}\\
&\times\varphi_{i,s+1}\xi_{i,s+1}^T\bar{K}_{i,s+1}^T\big\},\\
L_2\triangleq&\mathbb{E}\big\{[(1-\varphi_{i,s+1})\Upsilon_{i,s+1}-(1-\bar{\varphi}_i)\psi_{i,s+1}]\bar{K}_{i,s+1}\\
&\times C_{i,s+1}x_{i,s+1}\varphi_{i,s+1}\xi_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}.
\end{aligned}
$$

Lemma 2 implies

$$
\begin{aligned}
&-L_1-L_1^T\\
\le&\beta_2\mathbb{E}\big\{(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})e_{i,s+1|s}\\
&\times e_{i,s+1|s}^T(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})^T\big\}\\
&+\beta_2^{-1}\mathbb{E}\big\{\varphi_{i,s+1}^2\bar{K}_{i,s+1}\xi_{i,s+1}\xi_{i,s+1}^T\bar{K}_{i,s+1}^T\big\},\\
&L_2+L_2^T\\
\le&\beta_3\mathbb{E}\big\{[(1-\varphi_{i,s+1})\Upsilon_{i,s+1}-(1-\bar{\varphi}_i)\psi_{i,s+1}]^2\\
&\times\bar{K}_{i,s+1}C_{i,s+1}x_{i,s+1}x_{i,s+1}^TC_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}\\
&+\beta_3^{-1}\mathbb{E}\left\{\varphi_{i,s+1}^2\bar{K}_{i,s+1}\xi_{i,s+1}\xi_{i,s+1}^T\bar{K}_{i,s+1}^T\right\}.
\end{aligned}
$$

Then, (24) becomes

$$
\begin{aligned}
&P_{i,s+1|s+1}\\
=&(1+\beta_2)\mathbb{E}\big\{(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})e_{i,s+1|s}\\
&\times e_{i,s+1|s}^T(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})^T\big\}\\
&+(1+\beta_3)\mathbb{E}\big\{[(1-\varphi_{i,s+1})\Upsilon_{i,s+1}-(1-\bar{\varphi}_i)\psi_{i,s+1}]^2\\
&\times\bar{K}_{i,s+1}C_{i,s+1}x_{i,s+1}x_{i,s+1}^TC_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}\\
&+\mathbb{E}\big\{[(1-\varphi_{i,s+1})\Upsilon_{i,s+1}]^2\bar{K}_{i,s+1}D_{i,s+1}\nu_{i,s+1}\\
&\times\nu_{i,s+1}^TD_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}+(1+\beta_2^{-1}+\beta_3^{-1})\\
&\times\mathbb{E}\big\{\varphi_{i,s+1}^2\bar{K}_{i,s+1}\xi_{i,s+1}\xi_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}.
\end{aligned}\tag{25}
$$

Moreover, it is easy to see that

$$
\begin{aligned}
&\mathbb{E}\{x_{i,s+1}x_{i,s+1}^T\}\\
=&\mathbb{E}\big\{(e_{i,s+1|s}+\hat{x}_{i,s+1|s})(e_{i,s+1|s}+\hat{x}_{i,s+1|s})^T\big\}\\
\le&(1+\tilde{\beta})P_{i,s+1|s}+(1+\tilde{\beta}^{-1})\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^T.
\end{aligned}\tag{26}
$$

Noting $\mathbb{E}\{\Delta_{i,s+1}\}=0$ and $\bar{K}_{i,s+1}\triangleq K_{i,s+1}+\Delta_{i,s+1}$, one has

$$
\begin{aligned}
&\mathbb{E}\big\{(I-\bar{K}_{i,s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})e_{i,s+1|s}e_{i,s+1|s}^T\\
&\times(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})^T\big\}\\
=&\mathbb{E}\big\{e_{i,s+1|s}e_{i,s+1|s}^T\big\}-\mathbb{E}\big\{(1-\bar{\varphi}_i)\psi_{i,s+1}e_{i,s+1|s}\\
&\times e_{i,s+1|s}^TC_{i,s+1}^TK_{i,s+1}^T\big\}-\mathbb{E}\big\{(1-\bar{\varphi}_i)\psi_{i,s+1}\\
&\times K_{i,s+1}C_{i,s+1}e_{i,s+1|s}e_{i,s+1|s}^T\big\}+\mathbb{E}\big\{(1-\bar{\varphi}_i)^2\\
&\times\psi_{i,s+1}^2K_{i,s+1}C_{i,s+1}e_{i,s+1|s}e_{i,s+1|s}^TC_{i,s+1}^TK_{i,s+1}^T\big\}\\
&+\mathbb{E}\big\{(1-\bar{\varphi}_i)^2\psi_{i,s+1}^2\Delta_{i,s+1}C_{i,s+1}e_{i,s+1|s}e_{i,s+1|s}^T\\
&\times C_{i,s+1}^T\Delta_{i,s+1}^T\big\}.
\end{aligned}\tag{27}
$$

Next, $\mathbb{E}\{\Delta_{i,s}\Delta_{i,s}^T\}\le\gamma_iI$ indicates

$$
\begin{aligned}
&\mathbb{E}\big\{(I-\bar{K}_{i,s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})e_{i,s+1|s}e_{i,s+1|s}^T\\
&\times(I-\bar{K}_{s+1}(1-\bar{\varphi}_i)\psi_{i,s+1}C_{i,s+1})^T\big\}\\
\le&P_{i,s+1|s}-(1-\bar{\varphi}_i)\psi_{i,s+1}P_{i,s+1|s}C_{i,s+1}^TK_{i,s+1}^T\\
&-(1-\bar{\varphi}_i)\psi_{i,s+1}K_{i,s+1}C_{i,s+1}P_{i,s+1|s}\\
&+(1-\bar{\varphi}_i)^2\psi_{i,s+1}^2K_{i,s+1}C_{i,s+1}P_{i,s+1|s}C_{i,s+1}^TK_{i,s+1}^T\\
&+(1-\bar{\varphi}_i)^2\psi_{i,s+1}^2\lambda_{\max}(C_{i,s+1}P_{i,s+1|s}C_{i,s+1}^T)\gamma_iI.
\end{aligned}\tag{28}
$$

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Similarly, we have

$$\begin{aligned}&\mathbb{E}\big\{[(1-\varphi_{i,s+1})\Upsilon_{i,s+1}-(1-\bar{\varphi}_i)\psi_{i,s+1}]^2\bar{K}_{i,s+1}\\&\times C_{i,s+1}x_{i,s+1}x_{i,s+1}^TC_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}\\\le&(1-\bar{\varphi}_i)\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]K_{i,s+1}C_{i,s+1}P_{i,s+1|s}\\&\times C_{i,s+1}^TK_{i,s+1}^T+(1-\bar{\varphi}_i)\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]\\&\times K_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^TK_{i,s+1}^T\\&+(1-\bar{\varphi}_i)\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]\lambda_{\max}(C_{i,s+1}P_{i,s+1}\\&\times C_{i,s+1}^T)\gamma_iI+(1-\bar{\varphi}_i)\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]\\&\times\lambda_{\max}(C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^T)\gamma_iI\end{aligned}\tag{29}$$

and

$$\begin{aligned}&\mathbb{E}\big\{[(1-\varphi_{i,s+1})\Upsilon_{i,s+1}]^2\bar{K}_{i,s+1}D_{i,s+1}\nu_{i,s+1}\\&\times\nu_{i,s+1}^TD_{i,s+1}^T\bar{K}_{i,s+1}^T\big\}\\\le&(1-\bar{\varphi}_i)\psi_{i,s+1}K_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^TK_{i,s+1}^T\\&+(1-\bar{\varphi}_i)\psi_{i,s+1}\lambda_{\max}(D_{i,s+1}V_{i,s+1}D_{i,s+1}^T)\gamma_iI.\end{aligned}\tag{30}$$

From $\|\xi_{i,s}\|\le\bar{\xi}_i$, one has

$$\mathbb{E}\big\{\xi_{i,s}\xi_{i,s}^T\big\}\le\bar{\xi}_i^2I.\tag{31}$$

Summarizing the above derivations, we arrive at

$$\begin{aligned}&P_{i,s+1|s+1}\\\le&(1+\beta_2)P_{i,s+1|s}-(1+\beta_2)(1-\bar{\varphi}_i)\psi_{i,s+1}P_{i,s+1|s}\\&\times C_{i,s+1}^TK_{i,s+1}^T-(1+\beta_2)(1-\bar{\varphi}_i)\psi_{i,s+1}K_{i,s+1}\\&\times C_{i,s+1}P_{i,s+1|s}+(1+\beta_2)(1-\bar{\varphi}_i)^2\psi_{i,s+1}^2K_{i,s+1}\\&\times C_{i,s+1}P_{i,s+1|s}C_{i,s+1}^TK_{i,s+1}^T+(1+\beta_3)(1+\tilde{\beta})\\&\times(1-\bar{\varphi}_i)\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]K_{i,s+1}C_{i,s+1}\\&\times P_{i,s+1|s}C_{i,s+1}^TK_{i,s+1}^T+(1+\beta_3)(1+\tilde{\beta})(1-\bar{\varphi}_i)\\&\times\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]\lambda_{\max}(C_{i,s+1}P_{i,s+1|s}\\&\times C_{i,s+1}^T)\gamma_iI+(1+\beta_2)(1-\bar{\varphi}_i)^2\psi_{i,s+1}^2\lambda_{\max}(C_{i,s+1}\\&\times P_{i,s+1|s}C_{i,s+1}^T)\gamma_iI+(1+\beta_3)(1+\tilde{\beta})\big[(1-\bar{\varphi}_i)\\&\times\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]\big]K_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\\&\times\hat{x}_{i,s+1|s}^TC_{i,s+1}^TK_{i,s+1}^T+(1+\beta_3)(1+\tilde{\beta})\\&\times\big[(1-\bar{\varphi}_i)\psi_{i,s+1}[1-(1-\bar{\varphi}_i)\psi_{i,s+1}]\big]\\&\times\lambda_{\max}(C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^T)\gamma_iI\\&+(1-\bar{\varphi}_i)\psi_{i,s+1}K_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^TK_{i,s+1}^T\\&+(1-\bar{\varphi}_i)\psi_{i,s+1}\lambda_{\max}(D_{i,s+1}V_{i,s+1}D_{i,s+1}^T)\gamma_iI\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_iK_{i,s+1}K_{i,s+1}^T\bar{\xi}_i^2I\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\bar{\xi}_i^2\gamma_iI.\end{aligned}\tag{32}$$

Substituting (18) into (32) yields

$$\begin{aligned}&P_{i,s+1|s+1}\\\le&(1+\beta_2)P_{i,s+1|s}-(1+\beta_2)\tau_{i,s+1}P_{i,s+1|s}C_{i,s+1}^TK_{i,s+1}^T\\&-(1+\beta_2)\tau_{i,s+1}K_{i,s+1}C_{i,s+1}P_{i,s+1|s}\\&+(\sigma_{i,s+1}+\phi_{i,s+1})K_{i,s+1}C_{i,s+1}P_{i,s+1|s}C_{i,s+1}^TK_{i,s+1}^T\\&+(\sigma_{i,s+1}+\phi_{i,s+1})\lambda_{\max}(C_{i,s+1}P_{i,s+1|s}C_{i,s+1}^T)\gamma_iI\\&+\phi_{i,s+1}K_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^TK_{i,s+1}^T\\&+\phi_{i,s+1}\lambda_{\max}(C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^T)\gamma_iI\\&+\tau_{i,s+1}K_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^TK_{i,s+1}^T\\&+\tau_{i,s+1}\lambda_{\max}(D_{i,s+1}V_{i,s+1}D_{i,s+1}^T)\gamma_iI\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_iK_{i,s+1}K_{i,s+1}^T\bar{\xi}_i^2I\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\bar{\xi}_i^2\gamma_iI.\end{aligned}\tag{33}$$

Since $P_{i,s|s}\le\bar{\Re}_{i,s|s}$, by comparing (16) with (23), we have $P_{i,s+1|s}\le\bar{\Re}_{i,s+1|s}$ which, together with (17) and (33), further implies $P_{i,s+1|s+1}\le\bar{\Re}_{i,s+1|s+1}$. ■

Have obtained the upper bound $\bar{\Re}_{i,s+1|s+1}$, the estimator gains are designed by minimizing $\bar{\Re}_{i,s+1|s+1}$ at each time instant.

Theorem 2: Bound $\bar{\Re}_{i,s+1|s+1}$ of the EEC is minimized by designing the following estimator gains:

$$K_{i,s+1}=\Psi_{i,s+1}\Lambda_{i,s+1}^{-1}\tag{34}$$

where

$$\begin{aligned}\Psi_{i,s+1}\triangleq&(1+\beta_2)\tau_{i,s+1}P_{i,s+1|s}C_{i,s+1}^T,\\\Lambda_{i,s+1}\triangleq&(\sigma_{i,s+1}+\phi_{i,s+1})C_{i,s+1}P_{i,s+1|s}C_{i,s+1}^T\\&+\phi_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^T\\&+\tau_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^T\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\bar{\xi}_i^2I.\end{aligned}\tag{35}$$

Proof: The trace of the $\bar{\Re}_{i,s+1|s+1}$ can be computed as follows:

$$\begin{aligned}&\mathrm{tr}\{\bar{\Re}_{i,s+1|s+1}\}\\=&(1+\beta_2)\mathrm{tr}\{\bar{\Re}_{i,s+1|s}\}-(1+\beta_2)\tau_{i,s+1}\mathrm{tr}\{\bar{\Re}_{i,s+1|s}C_{i,s+1}^T\\&\times K_{i,s+1}^T\}-(1+\beta_2)\tau_{i,s+1}\mathrm{tr}\{K_{i,s+1}C_{i,s+1}\bar{\Re}_{i,s+1|s}\}\\&+(\sigma_{i,s+1}+\phi_{i,s+1})\mathrm{tr}\{K_{i,s+1}C_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^TK_{i,s+1}^T\}\\&+(\sigma_{i,s+1}+\phi_{i,s+1})\lambda_{\max}(C_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T)\gamma_i\\&+\phi_{i,s+1}\mathrm{tr}\{K_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^TK_{i,s+1}^T\}\\&+\phi_{i,s+1}\lambda_{\max}(C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^T)\gamma_i\\&+\tau_{i,s+1}\mathrm{tr}\{K_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^TK_{i,s+1}^T\}\\&+\tau_{i,s+1}\lambda_{\max}(D_{i,s+1}V_{i,s+1}D_{i,s+1}^T)\gamma_i\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\mathrm{tr}\{K_{i,s+1}K_{i,s+1}^T\}\bar{\xi}_i^2\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\bar{\xi}_i^2\gamma_i.\end{aligned}\tag{36}$$

Taking the partial derivative of $\mathrm{tr}\{\bar{\Re}_{i,s+1|s+1}\}$ regarding the estimator gain $K_{i,s+1}$ yields

$$\begin{aligned}&\frac{\partial\mathrm{tr}(\bar{\Re}_{i,s+1|s+1})}{\partial K_{i,s+1}}\\=&-2(1+\beta_2)\tau_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T\\&+2(\sigma_{i,s+1}+\phi_{i,s+1})K_{i,s+1}C_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T\\&+2\phi_{i,s+1}K_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^TC_{i,s+1}^T\\&+2\tau_{i,s+1}K_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^T\\&+2(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\bar{\xi}_i^2K_{i,s+1}.\end{aligned}\tag{37}$$

The gain parameter $K_{i,s+1}$ can be determined by letting

$$\frac{\partial\mathrm{tr}(\bar{\Re}_{i,s+1|s+1})}{\partial K_{i,s+1}}=0,$$

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i.e.,

$$\begin{aligned}K_{i,s+1} =&(1+\beta_2)\tau_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T\\&\times\big\{(\sigma_{i,s+1}+\phi_{i,s+1})C_{i,s+1}\bar{\Re}_{i,s+1|s}C_{i,s+1}^T\\&+\phi_{i,s+1}C_{i,s+1}\hat{x}_{i,s+1|s}\hat{x}_{i,s+1|s}^T C_{i,s+1}^T\\&+\tau_{i,s+1}D_{i,s+1}V_{i,s+1}D_{i,s+1}^T\\&+(1+\beta_2^{-1}+\beta_3^{-1})\bar{\varphi}_i\bar{\xi}_i^2 I\big\}^{-1},\end{aligned}\tag{38}$$

which ends the proof. ■

Remark 4: We have addressed the recursive estimation problem for a type of CNs with EHSs subject to deception attacks. Recursive calculation has been novelly implemented for EEC bounds that are minimized by designing gains. By taking the system complexities (e.g. EHSs, deception attacks and parameter perturbations) into consideration, the developed approach not only provides the online estimation calculation but also has a certain level of resilience. The distinguished novelties of this paper are mainly twofold: 1) the state estimation problem is new in that it considers both EHSs and deception attacks within CNs under the influence of perturbed estimator parameters; and 2) a novel resilient estimator is proposed that utilizes attack-affected measurements with gains obtained recursively.

IV. An Illustrative Example

Consider a nonlinear CN composed of three nodes. $\Gamma = \mathrm{diag}\{1.5, 1.5, 1.5\}$ and

$$\Theta=\begin{bmatrix}-0.3 & 0.1 & 0.2\\ 0.1 & -0.3 & 0.2\\ 0.2 & 0.1 & -0.3\end{bmatrix}.$$

Other system matrices are

$$B_{1,s}=\begin{bmatrix}0.732\\ 0.820+0.050\sin(s)\\ 0.710\end{bmatrix},$$

$$B_{2,s}=\begin{bmatrix}0.827\\ 0.837+0.052\sin(s)\\ 0.653\end{bmatrix},$$

$$B_{3,s}=\begin{bmatrix}0.662\\ 0.562+0.018\sin(s)\\ 0.824\end{bmatrix}.$$

$$C_{1,s}=\begin{bmatrix}0.532 & 0.854+0.010\sin(s) & 0.628\\ 0.835 & 0.653+0.010\sin(s) & 0.727\end{bmatrix},$$

$$C_{2,s}=\begin{bmatrix}0.637 & 0.535+0.011\sin(s) & 0.622\\ 0.553 & 0.753+0.015\sin(s) & 0.824\end{bmatrix},$$

$$C_{3,s}=\begin{bmatrix}0.833 & 0.257+0.021\sin(s) & 0.428\\ 0.437 & 0.375+0.032\sin(s) & 0.623\end{bmatrix},$$

$$D_{1,s}=0.253+0.010\cos(s),$$

$$D_{2,s}=0.354+0.010\cos(s),$$

$$D_{3,s}=0.297+0.010\cos(s).$$

The nonlinear function is chosen as follows:

$$f(x_{i,s})=\begin{bmatrix}0.17\sin(x_{i1,s})\\ 0.16\sin(x_{i2,s})\\ 0.16\sin(x_{i3,s})\end{bmatrix}.$$

TABLE I
The Statistical Characteristics of $\psi_{i,s}$ and $\chi_{i,s}$

s	1	2	3	4	$\cdots$
$\psi_{1,s}$	1	0.8647	0.8840	0.8895	$\cdots$
$\psi_{2,s}$	1	0.8722	0.8946	0.9009	$\cdots$
$\psi_{3,s}$	1	0.8792	0.9039	0.9114	$\cdots$
$\chi_{1,s}$	$\begin{bmatrix}0\\0\\0\\1\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0.1353\\0.2707\\0.2707\\0.1804\\0.0902\\0.0527\\0.0000\end{bmatrix}$	$\begin{bmatrix}0.1160\\0.2442\\0.2636\\0.1933\\0.1078\\0.0628\\0.0123\end{bmatrix}$	$\begin{bmatrix}0.1105\\0.2358\\0.2589\\0.1953\\0.1135\\0.0674\\0.0186\end{bmatrix}$	$\cdots$
$\chi_{2,s}$	$\begin{bmatrix}0\\0\\0\\1\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0.1278\\0.2556\\0.2556\\0.1854\\0.1102\\0.0654\\0.0000\end{bmatrix}$	$\begin{bmatrix}0.1054\\0.2248\\0.2472\\0.1977\\0.1280\\0.0782\\0.0187\end{bmatrix}$	$\begin{bmatrix}0.0991\\0.2145\\0.2408\\0.1988\\0.1339\\0.0841\\0.0288\end{bmatrix}$	$\cdots$
$\chi_{3,s}$	$\begin{bmatrix}0\\0\\0\\1\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0.1208\\0.2416\\0.2416\\0.1914\\0.1102\\0.0944\\0.0000\end{bmatrix}$	$\begin{bmatrix}0.0961\\0.2055\\0.2302\\0.2017\\0.1316\\0.1053\\0.0297\end{bmatrix}$	$\begin{bmatrix}0.0886\\0.1931\\0.2217\\0.2012\\0.1386\\0.1111\\0.0457\end{bmatrix}$	$\cdots$

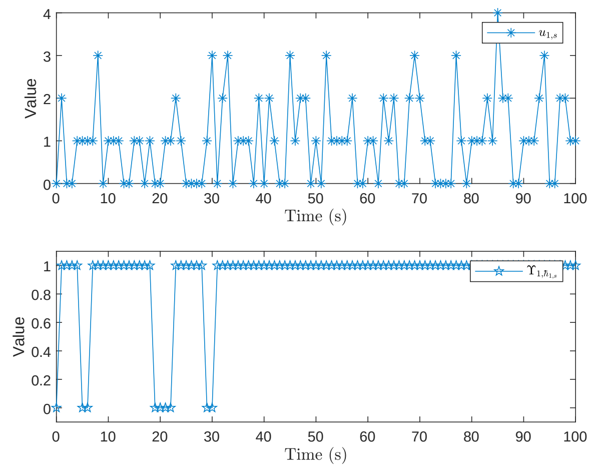

Fig. 2. Energy consumption and harvested of $x_{1,s}$.

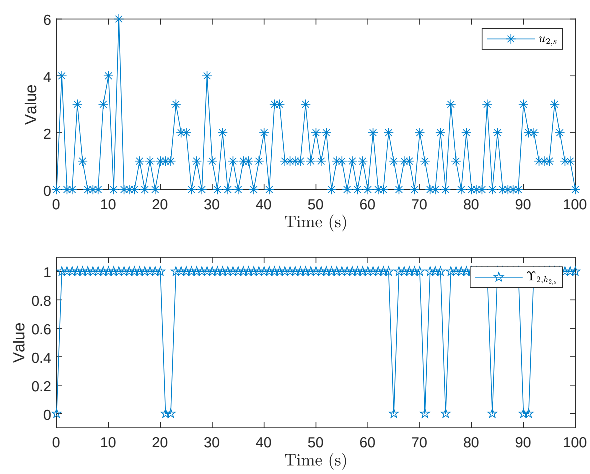

Fig. 3. The energy consumption and energy harvested of $x_{2,s}$.

It is easy to see that $f(x_s)$ satisfies (2) with $\alpha = 0.17$.

The covariances of the measurement and process noise for

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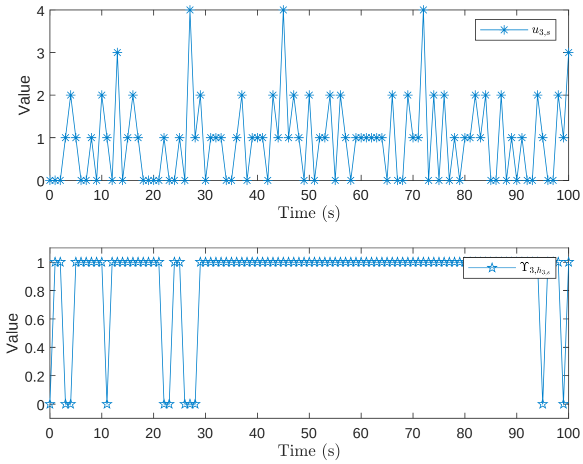

Fig. 4. The energy consumption and energy harvested of $x_{3,s}$.

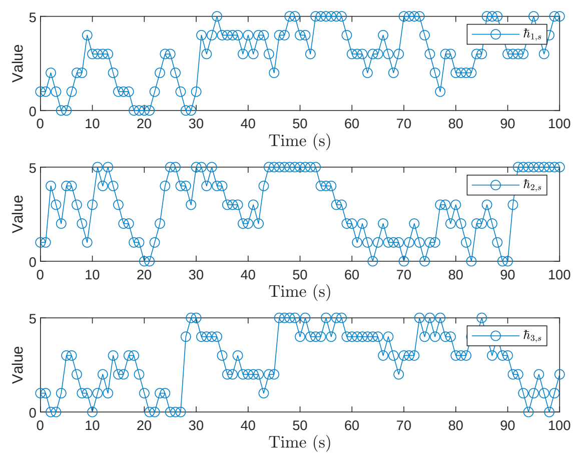

Fig. 5. The energy stored in the three batteries at each moment.

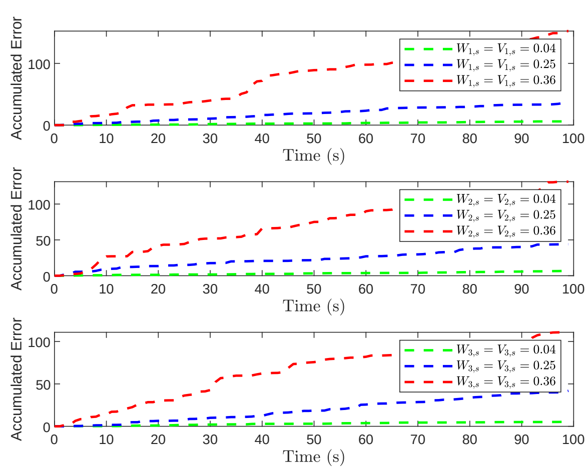

Fig. 6. Accumulated Errors for $x_{i,s}$ $(i = 1, 2, 3)$ under different $W_{i,s}$ and $V_{i,s}$ $(i = 1, 2, 3)$.

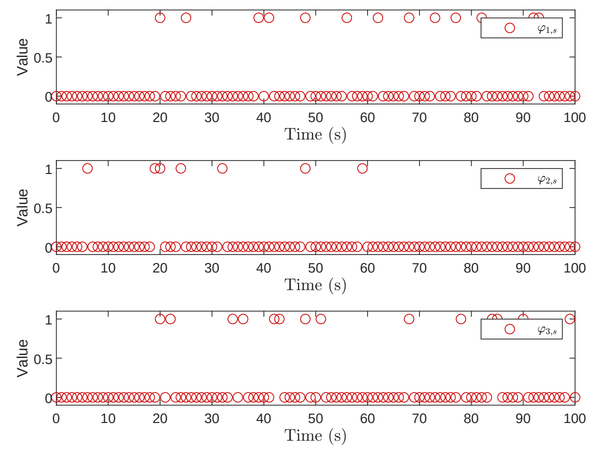

Fig. 7. Attack instant of the i-th node.

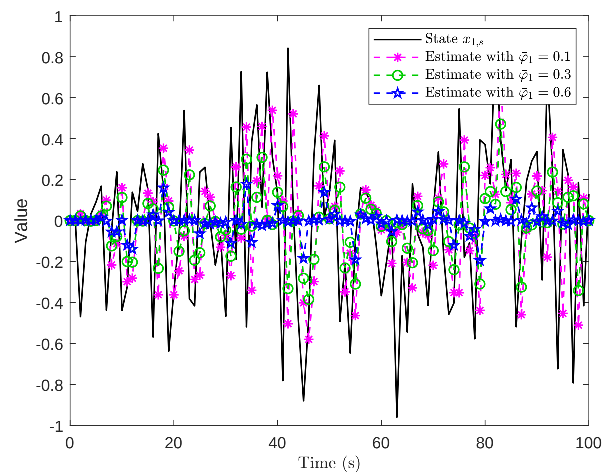

Fig. 8. The state $x_{1,s}$ and its estimations with different $\bar{\varphi}_1$ values.

the i-th node are selected as $V_{i,s} = 0.25$ and $W_{i,s} = 0.4$, respectively. The initial states and covariances are chosen as

$$x_{1,0} = \begin{bmatrix} 0.12 \\ 0.16 \\ 0.16 \end{bmatrix}, \quad P_{1,0} = 0.015I,$$

$$x_{2,0} = \begin{bmatrix} 0.12 \\ 0.16 \\ 0.16 \end{bmatrix}, \quad P_{2,0} = 0.015I,$$

$$x_{3,0} = \begin{bmatrix} 0.12 \\ 0.16 \\ 0.16 \end{bmatrix}, \quad P_{3,0} = 0.015I$$

where $x_{i,s} = \begin{bmatrix} x_{i,s}^1 & x_{i,s}^2 & x_{i,s}^3 \end{bmatrix}^T$ $(i = 1, 2, 3)$.

For node i, suppose that $\Phi_i = 5$ (i.e., a maximum energy storage capacity of 5 units) and $\hbar_{i,0} = 1$ (i.e., an initial energy storage of 1 unit). $u_{i,s}$ (the amount of energy harvested) is assumed to obey the Poisson process:

$$\text{Prob}\{u_{i,s} = \pi\} = \frac{\varsigma^\pi \exp(-\varsigma)}{\pi!}$$

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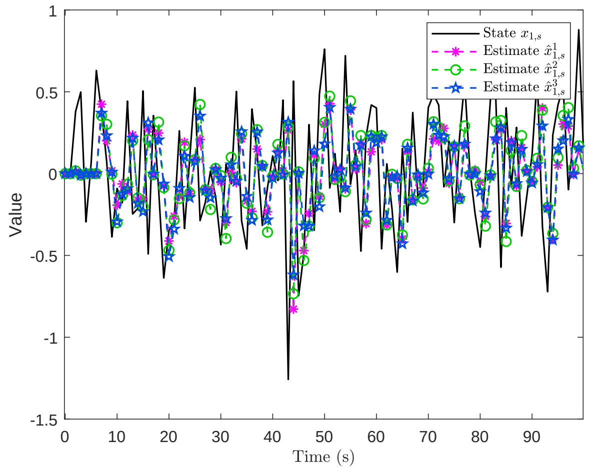

Fig. 9. The state $x_{1,s}$ and its estimations.

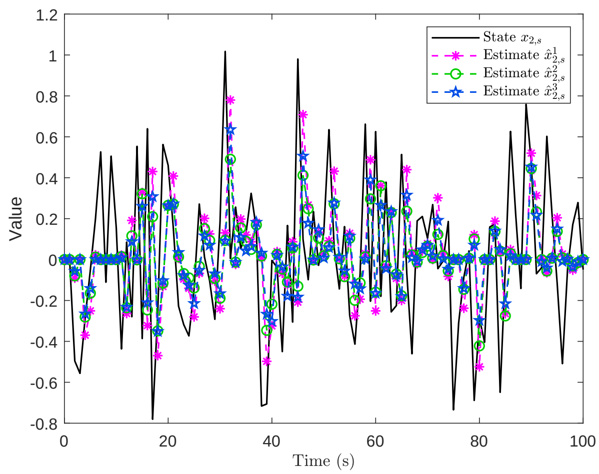

Fig. 10. The state $x_{2,s}$ and its estimations.

with parameter $\varsigma = 1$. According to (14), Table I provides values of $\psi_{i,s}$ $(i = 1, 2, 3)$ (the expectation of the successful measurement transmission), along with $\chi_{i,s}$ $(i = 1, 2, 3)$ (the probability distribution of sensor energy levels). The parameters $\bar{\xi}_i$ $(i = 1, 2, 3)$ are $\bar{\xi}_i = 0.10$. Attack probabilities are $\bar{\varphi}_1 = 0.15$, $\bar{\varphi}_2 = 0.10$, and $\bar{\varphi}_3 = 0.12$.

TABLE II
ACCUMULATED ESTIMATION ERROR UNDER DIFFERENT ς

Energy Harvesting Parameter ς	0.2	0.5	1.0
Accumulated Estimation Error Ω_{sum}	190.767	110.024	40.781
Accumulated Estimation Error Ω_{sum}	180.534	110.953	40.464
Accumulated Estimation Error Ω_{sum}	190.685	100.004	40.835

The results of EEC bounds and gains are presented in Figs. 2–13 and Table II. Figs. 2–4 display the values of $u_{i,s}$ and $\Upsilon_{i,\hbar_{i,s}}$ $(i = 1, 2, 3)$. $\hbar_{i,s}$ is depicted in Fig. 5. Specifically, to illustrate the influence of noise and the parameter ς on the

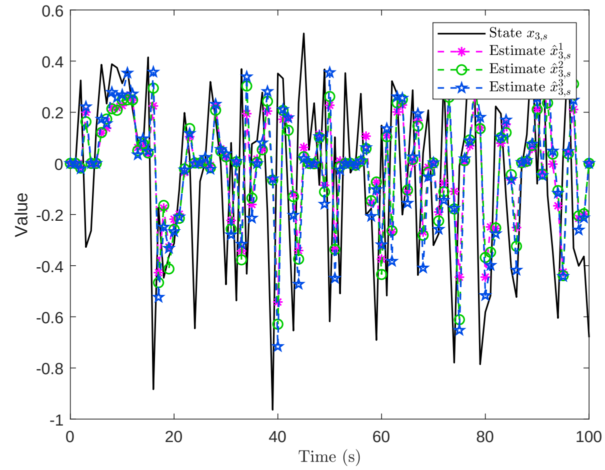

Fig. 11. The state $x_{3,s}$ and its estimations.

estimation performance, we define the accumulated error by

$$\Omega_{\text{sum}} \triangleq \sum_{s=0}^{s_{\max}} e^T_{s|s} e_{s|s}.$$

Fig. 6 is presented to show the accumulated estimation error obtained with varying noise covariances. It can be seen that the greater the noise covariance, the larger the accumulated estimation error. Table II presents the accumulated estimation error under different values of ς. It is observed that, as the parameter ς increases, the accumulated estimation error decreases, which conforms to the fact that estimation performance can be naturally improved by harvesting more energy.

Fig. 7 shows the instant of attack for the i-th node. Fig. 8 presents the estimation error of node 1 (i.e., $e_{1,s|s}$) under different values of $\bar{\varphi}_1$. It is observed that a larger $\bar{\varphi}_1$ (i.e., a higher probability of an attack occurring) leads to a larger error, which conforms to that a greater success rate of a deception attack decreases the estimation performance. Figs. 9–11 depict state trajectories and estimates.

To verify the applicability of the proposed method, we consider different topological cases, i.e.,

$$\Theta = \begin{bmatrix} -0.2 & 0.1 & 0.1 \\ 0.1 & -0.2 & 0.1 \\ 0.1 & 0.1 & -0.2 \end{bmatrix},$$

and the state trajectories and estimates are given in Fig. 12. Meanwhile, to demonstrate the effectiveness and advantages of the proposed estimation algorithm, we have included a comparative analysis with the existing method from [32], as shown in Fig. 13. The results indicate that our approach achieves better estimation performance under the same settings, primarily because it explicitly accounts for the effects of both attacks and energy harvesting in the theoretical design.

In conclusion, all simulations indicate the effectiveness of the proposed state estimation approach.

V. CONCLUSION

We have researched into a topic of resilient estimation within CNs equipped with EHSs whose measurements are

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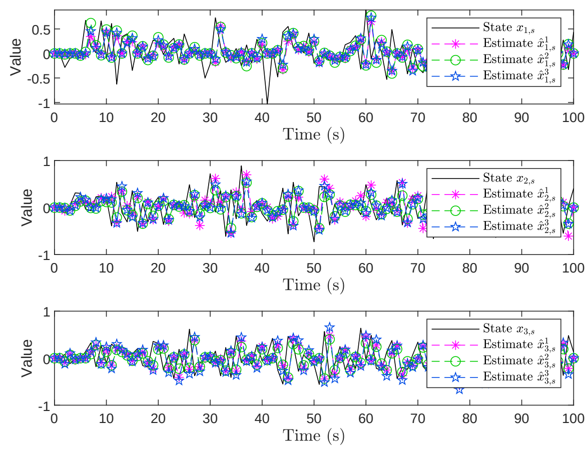

Fig. 12. The state and their estimations under another topological cases.

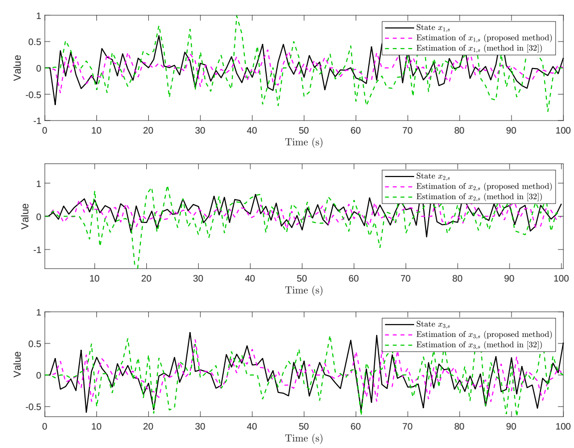

Fig. 13. The comparison with the existing literature.

transmitted over a network vulnerable to deception attacks. A recursive resilient state estimation strategy has been proposed to deal with parameter fluctuations caused by component ageing and various reasons. Then, EEC bounds and estimator gains have been computed recursively. An illustrative example has been provided ultimately to demonstrate this strategy's efficacy. Future research directions include: 1) addressing the fault estimator design issue in sensor networks with EHS, and 2) extending the framework to accommodate various cyber-attacks, such as replay and denial-of-service attacks [45], [55]–[57].

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