This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

Multi-Sensor Particle Filtering for Nonlinear Complex Networks With Heterogeneous Measurements Under Non-Gaussian Noises

Weihao Song, Zidong Wang, Zhongkui Li, and Hongli Dong

***Abstract*—In this paper, the multi-sensor particle filtering problem is investigated for a class of nonlinear complex networks with multi-rate heterogeneous measurements. The underlying complex networks are subject to non-Gaussian noises and randomly switching couplings, while the multi-rate heterogeneous measurements (including fast-rate binary measurements and slow-rate integral measurements) are transmitted to remote filters via imperfect wireless communication channels. Both the deterministic and stochastic channel gains, along with possible transmission failures, are taken into account to characterize the properties of wireless communication channels. The purpose of this paper is to propose a channel-related filtering scheme within the particle filtering framework to address these engineering-oriented complexities. To achieve this, a mixture distribution is established to reflect the effects of randomly switching couplings and generate new particle candidates. By utilizing the Monte Carlo approximation method, two types of update expressions for importance weights are explicitly derived based on the channel properties and the likelihood functions. Finally, numerical simulations are presented to demonstrate the viability and effectiveness of the proposed particle filtering algorithms.**

***Index Terms*—Nonlinear complex network, particle filtering, non-Gaussian noises, binary measurements, integral measurements, channel gain, packet dropout.**

I. Introduction

The past several decades have witnessed a tremendous amount of research attention devoted to the complex networks owing to their remarkable capability in characterizing large-scale real-world systems. Representative examples of these ubiquitous large-scale systems include, but are not limited to, power grids, genetic regulatory networks, financial networks, and air cargo transport networks [1]–[5]. Typically, a complex network is composed of a cluster of coupled units/nodes, whose rich dynamics, when combined with various topology structures and coupling strengths, enable the complex network to exhibit a diversity of intricate dynamical behaviors (e.g., synchronization). In order to better understand and exploit these behaviors, the dynamics analysis problem has gradually become a fundamental and crucial topic in the study of complex networks, leading to a substantial body of elegant results in the literature [6]–[9]. For instance, the issue of fixed-time synchronization has been investigated in [10] for a particular class of complex networks with impulsive effects.

It is widely acknowledged that state estimation has long been one of the paramount problems in the fields of control theory and signal processing. Regarding complex networks, the corresponding state estimation (or filtering) problem also plays a critical role since accurate state information, typically inaccessible due to technical or budgetary constraints, is essential for uncovering inherent network characteristics and executing practical missions. In response to this need, a substantial body of research has emerged, focusing on pragmatic state estimation (or filtering) schemes for various types of complex networks [11]–[14]. For instance, the robust state estimation problem has been investigated in [15] for a class of discrete-time Markovian neural networks experiencing mode-dependent delays and inconstant measurements. A set-membership state estimation algorithm has been proposed in [16] for complex networks subject to unknown but bounded noises and attacks.

System nonlinearity and noise non-Gaussianity are two pervasive phenomena in practical engineering (e.g., in applications involving the unmanned aerial vehicle helicopters [17]), whose presence significantly increases the difficulty of estimator/filter design [18]–[21]. This is particularly relevant in the case of complex networks owing to the inherent coupling characteristics of node dynamics. Consequently, the majority of existing research is confined to scenarios involving specific nonlinearities and Gaussian/bounded noises; for example, see [22] for sector-bounded nonlinearities and norm-bounded noises, [23] for Lipschitz-type nonlinearities and Gaussian noises, and [24] for continuously differentiable nonlinearities and Gaussian noises. In addition, the phenomenon of randomly switching couplings, primarily caused by changes in network structures and external environments, has recently garnered some preliminary attention. For instance, a variance-constrained recursive estimator has been developed in [25]

This work was supported in part by the National Natural Science Foundation of China under Grants 62203016, 62425301, U2241214, 62373008, and 61933007, in part by the China Postdoctoral Science Foundation under Grant 2021TQ0009, in part by the Royal Society of the UK, and in part by the Alexander von Humboldt Foundation of Germany. *(Corresponding author: Zhongkui Li.)*

Weihao Song is with the School of Advanced Manufacturing and Robotics, Peking University, Beijing 100871, China, and also with the Department of Computer Science, Brunel University London, Uxbridge, Middlesex, UB8 3PH, United Kingdom. (Email: weihao.song@pku.edu.cn)

Zidong Wang is with the Department of Computer Science, Brunel University London, Uxbridge, Middlesex, UB8 3PH, United Kingdom. (Email: Zidong.Wang@brunel.ac.uk)

Zhongkui Li is with the School of Advanced Manufacturing and Robotics, Peking University, Beijing 100871, China. (Email: zhongkli@pku.edu.cn)

Hongli Dong is with the Artificial Intelligence Energy Research Institute, Northeast Petroleum University, Daqing 163318, China, and also with the Heilongjiang Provincial Key Laboratory of Networking and Intelligent Control, Northeast Petroleum University, Daqing 163318, China. (Email: shiningdhl@vip.126.com)

for stochastic complex networks with switching topology. In [26], the issue of fault estimation has been addressed for complex networks with randomly varying couplings. Nevertheless, to the best of the authors' knowledge, the filtering problem for generally nonlinear complex networks subject to randomly switching couplings and non-Gaussian noises has yet to receive sufficient research attention, which constitutes the primary motivation of this paper.

Recently, binary sensors have attracted increasing research interest as demonstrated by their successful applications in diverse fields such as chemical processes, target tracking, medical testing, system identification, and microelectronic fabrication [27]–[29]. It is worth noting that binary sensors can only generate one bit of information based on the size comparison between the measured variable and a threshold (typically determined by the physical sensing mechanism or the practical application requirements), making them naturally cost-efficient but at the expense of a significant loss of information. Thus, it is of both theoretical and practical interest to explore the design of state estimation (or filtering) schemes using binary measurements. In this regard, several noteworthy research results have been published in the literature [30]–[32]. For instance, the moving horizon estimation and set-membership state estimation problems have been explored in [33] and [34], respectively, for linear discrete-time systems subject to binary measurements as well as unknown but bounded noises. However, when it comes to nonlinear and non-Gaussian complex networks, the corresponding filtering problem has yet to receive adequate attention.

In most of the existing literature addressing the state estimation (or filtering) problem, there is an implicit yet prevalent assumption that sensor measurements depend solely on the current system state information and can be obtained instantaneously [35]–[38]. However, such an assumption proves to be unrealistic in many practical industrial applications constrained by technical/budgetary factors. For instance, in some chemical processes, certain measurement outputs (e.g., sample concentration) are actually functions of the integral of system states over a given time window, leading to the phenomenon of integral measurements [39], [40]. Integral measurements are typically available at a slower rate than regular measurements, primarily due to the time required for data collection and processing [41]. To date, several representative results have been reported concerning the state estimation (or filtering) issues in the presence of slow-rate integral measurements, see e.g., [42], [43] and references therein. It should also be noted that little attention has been given to the design of filters for complex networks under such conditions, let alone the coexistence of binary measurements.

As a crucial component of networked systems, wireless communication technology has gained unprecedented popularity in recent years due primarily to its significant advantages in terms of infrastructure installation and maintenance, cost, flexibility, and reliability [44]–[46]. It is important to note that in real-world engineering, wireless communication channels are often imperfect due to physical and/or environmental constraints, and the messages transmitted over such channels are inevitably affected by noise, signal fading, and even packet dropouts [47]–[49]. For example, in an autonomous vehicle system, the signal transmissions over an open communication channel are usually susceptible to cyber-attacks [50]. Clearly, these channel-induced impairments, if left untreated, are likely to cause significant performance degradation. Therefore, it is practically sensible to account for the conditions of wireless communication channels and design channel-related state estimation (or filtering) strategies accordingly. In this context, channel-aware tracking schemes have been proposed in [51], where two types of channel gains were considered, along with multi-hop wireless sensor networks and quantized received-signal-strength measurements. Furthermore, in [52], the networked fusion estimation problem has been examined under the consideration of random parameter matrices and time-correlated channel noises.

Driven by the preceding discussions, this paper aims to address the multi-sensor filtering problem for a class of nonlinear complex networks subject to randomly switching couplings, multi-rate heterogeneous measurements, and non-Gaussian noises. In pursuing this goal, the following three pivotal difficulties must be overcome: 1) developing a concise yet applicable model for generally nonlinear and non-Gaussian complex networks that incorporates the phenomena of randomly switching couplings, multi-rate heterogeneous measurements, and channel-induced impairments; 2) devising reasonable schemes to handle the complexities introduced by the multi-rate heterogeneous measurements and the multi-source randomness; and 3) designing effective multi-sensor filtering algorithms to mitigate the combined effects of these factors. The purpose of this paper is, therefore, to propose efficient solutions to these challenges by addressing the channel-related multi-sensor filtering problem.

The primary contributions of this paper encompass the following three aspects: 1) compared with the existing results for complex networks [25], [26], the filtering problem under investigation is more comprehensive through addressing several engineering-oriented phenomena including randomly switching couplings, multi-rate heterogeneous measurements, and channel-induced impairments; 2) two explicit update expressions for the importance weights are established by incorporating various channel conditions and deriving the corresponding likelihood functions; and 3) channel-related particle filtering algorithms are developed for a general class of nonlinear and non-Gaussian complex networks, which impose minimal restrictions on system configuration and offer broad application prospects.

The remainder of this paper is structured as follows. Section II formulates the filter design problem for nonlinear and non-Gaussian complex networks with multi-rate heterogeneous measurements and imperfect measurement transmissions. In Section III, the channel-related particle filtering algorithms are designed by taking into account both deterministic and stochastic channel gains. Section IV provides simulation results to demonstrate the effectiveness of the proposed channel-related particle filtering schemes. Finally, Section V presents concluding remarks.

Notations : The notation used in this paper follows standard conventions. $\mathbb{R}^n$ represents the n-dimensional Euclidean vec-

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

tor space. The probability density function (PDF) of a random variable a is denoted by $p_a(\cdot)$, and $\Pr\{E\}$ stands for the occurrence probability of a discrete event E. For a Gaussian random variable a, its PDF is denoted by $\mathcal{N}(a;\mu_a,\Sigma_a)$, where μ_a and Σ_a are the mean and covariance, respectively. $x_{u:v}$ denotes the trajectory of x from time instant u to time instant v. $\mathrm{diag}\{x_1,x_2,\ldots,x_n\}$ stands for a diagonal matrix with diagonal elements $x_1,x_2,\ldots,x_n$. I indicates an identity matrix with appropriate dimensions. Other notations will be defined as necessary.

II. Problem Formulation

A. System Dynamics and Measurement Models

Consider a class of nonlinear complex networks with S coupled nodes and randomly switching couplings, where the dynamics of the r-th node is characterized as follows:

$$x_{k+1}^r = g^r(x_k^r) + (1-\eta_k)\left(\sum_{s=1}^{S}\theta_0^{rs}\Lambda_0 x_k^s\right) + \eta_k\left(\sum_{s=1}^{S}\theta_1^{rs}\Lambda_1 x_k^s\right) + \mu_k^r. \tag{1}$$

Here, $x_k^r \in \mathbb{R}^{n_x}$ stands for the local system state at time instant k; $\Theta_a = [\theta_a^{rs}]_{S\times S}$ $(a=0,1)$ describes the outer coupling configuration matrix with θ_a^{rs} denoting the strength between the r-th node and the s-th node; $\Lambda_a = \mathrm{diag}\{\lambda_{a,1},\lambda_{a,2},\ldots,\lambda_{a,n_x}\}$ $(a=0,1)$ denotes the inner coupling matrix; μ_k^r represents the process noise with known PDF $p_{\mu_k^r}(\cdot)$; $g^r(\cdot):\ \mathbb{R}^{n_x}\to\mathbb{R}^{n_x}$ is the known nonlinear function; and the random variable η_k, characterizing the switching couplings, has the following probability distribution:

$$\begin{cases}\Pr\{\eta_k=0\}=p_{\eta,0}\\ \Pr\{\eta_k=1\}=1-p_{\eta,0}\end{cases} \tag{2}$$

where $p_{\eta,0}$ is a known constant within the interval $[0,\ 1]$.

In order to estimate the state of the target plant (1), it is assumed that two types of measurements are available: fast-rate binary measurements and slow-rate integral measurements, as illustrated in Fig. 1. For the fast-rate binary measurements, the relationship between the measurement output and the system state at time instant k can be expressed as follows:

$$\bar{y}_k^{r,j} = f^{r,j}(x_k^r) + \omega_k^{r,j},\quad j=1,2,\ldots,J \tag{3}$$

$$\tilde{y}_k^{r,B,j} = \begin{cases}1, & \text{if } \bar{y}_k^{r,j} > \tau^{r,j};\\ -1, & \text{otherwise}\end{cases} \tag{4}$$

where $\bar{y}_k^{r,j}$ and $\tilde{y}_k^{r,B,j}\in\mathbb{R}$ represent, respectively, the original measurement and the binary output of the j-th fast-rate sensor for the r-th node; $f^{r,j}(\cdot):\ \mathbb{R}^{n_x}\to\mathbb{R}$ denotes the known and possibly nonlinear function; $\omega_k^{r,j}$ is the measurement noise with known PDF $p_{\omega_k^{r,j}}(\cdot)$; and $\tau^{r,j}$ denotes the threshold determining the value of binary output.

For the slow-rate integral measurements, the measurement equation associated with the r-th node is described as follows [43]:

$$\breve{x}_{t_i}^r = \sum_{s=t_{i-1}+1}^{t_i} H_s^r x_s^r \tag{5}$$

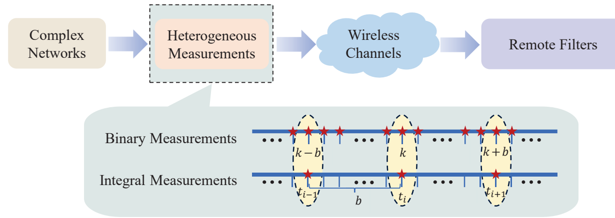


Fig. 1: Filtering problem with multi-rate heterogeneous measurements.

$$\tilde{y}_{t_i}^{r,I} = h^r(\breve{x}_{t_i}^r) + \nu_{t_i}^r \tag{6}$$

where $\tilde{y}_{t_i}^{r,I}\in\mathbb{R}^{n_y}$ denotes the integral measurement collected from time instant $t_{i-1}+1$ to t_i and $t_i = t_{i-1}+b$ with b being a positive integer greater than one, which specifies the time interval for data collection and processing; $H_s^r\in\mathbb{R}^{n_{\breve{x}}\times n_x}$ denotes the known matrix involved in the integral term $\breve{x}_{t_i}^r$; $h^r(\cdot):\ \mathbb{R}^{n_{\breve{x}}}\to\mathbb{R}^{n_y}$ is the known and possibly nonlinear function; and $\nu_{t_i}^r$ represents the measurement noise with known PDF $p_{\nu_{t_i}^r}(\cdot)$.

B. Measurement Transmissions Over Imperfect Channels

In practical scenarios, the communication channels (as depicted in Fig. 1) are typically imperfect, and data transmissions may experience fading. Furthermore, due to factors such as limited communication bandwidth and potential malicious cyber-attacks, packet dropouts might also occur during data transmission. To account for these issues, the measurements after transmission through the non-ideal channels can be characterized as follows:

$$\begin{aligned} y_k^{r,B,j} &= \alpha_k^{r,j} u_k^{r,j}\tilde{y}_k^{r,B,j} + \xi_k^{r,j},\quad j=1,2,\ldots,J\\ y_{t_i}^{r,I} &= \beta_{t_i}^r v_{t_i}^r \tilde{y}_{t_i}^{r,I} + \chi_{t_i}^r \end{aligned} \tag{7}$$

where $y_k^{r,B,j}$ and $y_{t_i}^{r,I}$ represent the available measurement information at the filter end; $u_k^{r,j}$ and $v_{t_i}^r$ describe the corresponding channel gains during the signal transmission; $\xi_k^{r,j}$ and $\chi_{t_i}^r$ stands for the additive channel noises with respective PDF $p_{\xi_k^{r,j}}(\cdot)$ and $p_{\chi_{t_i}^r}(\cdot)$. The terms $\alpha_k^{r,j}$ and $\beta_{t_i}^r$, introduced to capture the phenomenon of packet dropouts, are Bernoulli-distributed random variables with the following probability distribution:

$$\begin{cases}\Pr\{\alpha_k^{r,j}=1\}=\bar{\alpha}^{r,j}\\ \Pr\{\alpha_k^{r,j}=0\}=1-\bar{\alpha}^{r,j}\end{cases} \tag{8}$$

and

$$\begin{cases}\Pr\{\beta_{t_i}^r=1\}=\bar{\beta}^r\\ \Pr\{\beta_{t_i}^r=0\}=1-\bar{\beta}^r\end{cases} \tag{9}$$

where $\bar{\alpha}^{r,j}$ and $\bar{\beta}^r$ are known positive scalars within the interval $[0,\ 1]$.

Throughout this paper, the process noises μ_k^r, the measurement noises $\omega_k^{r,j}$ and $\nu_{t_i}^r$, the channel noises $\xi_k^{r,j}$ and $\chi_{t_i}^r$, the random variables $\alpha_k^{r,j}$ and $\beta_{t_i}^r$, and the channel gains $u_k^{r,j}$ and $v_{t_i}^r$ (if random) are mutually independent and also independent of the initial state x_0^r with PDF $p_{x_0^r}(\cdot)$.

Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

The purpose of this paper is to develop multi-sensor particle filtering algorithms for nonlinear complex networks with binary and integral measurements, addressing the challenges posed by randomly switching couplings, non-Gaussian noises, and packet dropouts. Specifically, the aim is to estimate the state of each node based on the available heterogeneous measurements, while accounting for the imperfections of the communication channels.

III. Design of Multi-Sensor Particle Filtering Algorithms

In this section, we will design two types of algorithms within the particle filtering framework based on the heterogeneous measurements and the specific channel conditions.

Before proceeding further, let us denote by Y_k^r the received measurements at time instant k ($k > 1$) for node r:

$$Y_k^r = \begin{cases} [(y_k^{r,B})^T \ (y_k^{r,I})^T]^T, & \text{if } \mathrm{mod}(k-1,b)=0; \\ y_k^{r,B}, & \text{otherwise} \end{cases} \tag{10}$$

where $y_k^{r,B} = [y_k^{r,B,1} \ y_k^{r,B,2} \ \cdots \ y_k^{r,B,J}]^T$. Moreover, we define $Y_1^r = y_1^{r,B}$ and set $t_0 = 1$ to avoid confusion. Accordingly, the available measurements for node r up to time instant k can be characterized as

$$Y_{1:k}^r = [(Y_1^r)^T \ (Y_2^r)^T \ \cdots \ (Y_k^r)^T]^T.$$

Due to the aforementioned engineering-oriented complexities, it is extremely challenging, if not infeasible, to derive an analytical expression for the posterior PDF of the states of interest, i.e., $p(x_{0:k}^r|Y_{1:k}^r)$. To address this, we employ the well-known sampling importance resampling particle filtering algorithm [53]. The fundamental idea of particle filtering is to approximate the posterior PDF using a set of weighted particles as follows:

$$p(x_{0:k}^r|Y_{1:k}^r) = \sum_{l=1}^{L} w_k^{r,\{l\}} \delta\left(x_{0:k}^r - x_{0:k}^{r,\{l\}}\right) \tag{11}$$

where L denotes the number of particle candidates, $\delta(\cdot)$ represents the Dirac delta function, $x_{0:k}^{r,\{l\}}$ is the l-th particle candidate sampled from the proposal density $q(x_{0:k}^r|Y_{1:k}^r)$ associated with the r-th node, and $w_k^{r,\{l\}}$ is the corresponding importance weight determined by

$$w_k^{r,\{l\}} = \frac{p(Y_k^r|x_{0:k}^{r,\{l\}}, Y_{1:k-1}^r)p(x_k^{r,\{l\}}|x_{k-1}^{r,\{l\}})}{q(x_k^{r,\{l\}}|x_{0:k-1}^{r,\{l\}}, Y_{1:k}^r)} w_{k-1}^{r,\{l\}}. \tag{12}$$

For ease of implementation, the proposal density is typically chosen as the state transition density, i.e.,

$$q(x_k^r|x_{0:k-1}^{r,\{l\}}, Y_{1:k}^r) = p(x_k^r|x_{k-1}^{r,\{l\}}). \tag{13}$$

It is apparent from the system dynamics (1) that the state evolution of the r-th node depends not only on its own previous state but also on the previous states of other coupled nodes, influenced by randomly switching couplings. Following the approach in [54], the states of other nodes are treated as inputs to the dynamics of the r-th node, and their corresponding values are approximated by their state estimates. Thus, the state transition density can be approximately expressed as:

$$p(x_k^r|x_{k-1}^{r,\{l\}}) \approx p(x_k^r|x_{k-1}^{r,\{l\}}, \hat{x}_{k-1}^s) \tag{14}$$

where $\hat{x}_{k-1}^s$ denotes the state estimate of the s-th node ($s \in \{1,2,\ldots,S\} \setminus \{r\}$) at time instant $k-1$.

Considering the randomly switching nature of the node couplings and the probability distribution (2), we can further express the state transition density as follows:

$$\begin{aligned} p(x_k^r|x_{k-1}^{r,\{l\}}, \hat{x}_{k-1}^s) = {} & p_{\eta,0}p(x_k^r|x_{k-1}^{r,\{l\}}, \hat{x}_{k-1}^s, \Theta_0, \Lambda_0) \\ & + (1-p_{\eta,0})p(x_k^r|x_{k-1}^{r,\{l\}}, \hat{x}_{k-1}^s, \Theta_1, \Lambda_1), \end{aligned} \tag{15}$$

which indicates that the generation of new particles is dependent on the statistical property of the randomly switching couplings.

Subsequently, we proceed to deduce two types of particle filtering strategies.

A. Particle Filtering Scheme with Deterministic Channel Gains

To begin with, let us consider the scenario where the channel gains $u_k^{r,j}$ and $v_{t_i}^r$ are deterministic and assumed to be known a priori. Under this circumstance, the likelihood function can be evaluated by separately considering the time instants with both fast-rate binary measurements and slow-rate integral measurements, as well as the time instants with only fast-rate binary measurements. For the former case, it should be pointed out that, due to the presence of slow-rate integral measurements, the current measurement Y_k^r is influenced not only by the current state x_k^r but also by the previous states $x_{k-b+1:k-1}^r$ within the collection window. Consequently, similar to the approach in [53], the likelihood function can be reformulated as follows:

$$p(Y_k^r|x_{0:k}^r, Y_{1:k-1}^r) = p(Y_k^r|x_{k-b+1:k}^r). \tag{16}$$

Under the assumption of mutually independent random noises, the likelihood function can be further factorized as follows:

$$\begin{aligned} p(Y_k^r|x_{k-b+1:k}^r) &= p(y_k^{r,I}|x_{k-b+1:k}^r) \prod_{j=1}^{J} p(y_k^{r,B,j}|x_{k-b+1:k}^r) \\ &= p(y_k^{r,I}|x_{k-b+1:k}^r) \prod_{j=1}^{J} p(y_k^{r,B,j}|x_k^r). \end{aligned} \tag{17}$$

Analogously, if the condition $\mathrm{mod}(k-1,b)=0$ does not hold, the likelihood function can be described by the following form:

$$p(Y_k^r|x_{k-b+1:k}^r) = \prod_{j=1}^{J} p(y_k^{r,B,j}|x_k^r). \tag{18}$$

Then, the next task is to determine the explicit expressions for $p(y_k^{r,B,j}|x_k^r)$ and $p(y_k^{r,I}|x_{k-b+1:k}^r)$ under the imperfect transmission channels with deterministic gains.

Based on the models (3) and (4) of fast-rate binary measurements, along with the transmission process characterized by (7) and (8), it follows that:

$$\begin{aligned} p(y_k^{r,B,j}|x_k^r) &= p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=1)\Pr\{\alpha_k^{r,j}=1\} \\ &\quad + p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=0)\Pr\{\alpha_k^{r,j}=0\} \\ &= \bar{\alpha}^{r,j} p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=1) \\ &\quad + (1-\bar{\alpha}^{r,j})p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=0). \end{aligned} \tag{19}$$

Now, we move on to calculate the term $p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=1)$ as follows:

$$\begin{aligned} & p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=1) \\ &= p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=1,\tilde{y}_k^{r,B,j}=1)\Pr\{\tilde{y}_k^{r,B,j}=1|x_k^r\} \\ &\quad + p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=1,\tilde{y}_k^{r,B,j}=-1)\Pr\{\tilde{y}_k^{r,B,j}=-1|x_k^r\} \\ &= p_{\xi_k^{r,j}}(y_k^{r,B,j}-u_k^{r,j})\Pr\{\tilde{y}_k^{r,B,j}=1|x_k^r\} \\ &\quad + p_{\xi_k^{r,j}}(y_k^{r,B,j}+u_k^{r,j})\Pr\{\tilde{y}_k^{r,B,j}=-1|x_k^r\} \end{aligned} \tag{20}$$

where the second equality follows from the expression of $y_k^{r,B,j}$ in (7), and the terms $\Pr\{\tilde{y}_k^{r,B,j}=1|x_k^r\}$ and $\Pr\{\tilde{y}_k^{r,B,j}=-1|x_k^r\}$ can be, respectively, determined by

$$\Pr\{\tilde{y}_k^{r,B,j}=1|x_k^r\} = 1-\Psi_{\omega_k^{r,j}}(\tau^{r,j}-f^{r,j}(x_k^r))$$

and

$$\Pr\{\tilde{y}_k^{r,B,j}=-1|x_k^r\} = \Psi_{\omega_k^{r,j}}(\tau^{r,j}-f^{r,j}(x_k^r))$$

where $\Psi_{\omega_k^{r,j}}(\cdot)$ denotes the cumulative distribution function.

On the other hand, it is not difficult to obtain that

$$p(y_k^{r,B,j}|x_k^r,\alpha_k^{r,j}=0) = p_{\xi_k^{r,j}}(y_k^{r,B,j}). \tag{21}$$

Then, substituting (19)-(21) into (18) gives rise to

$$\begin{aligned} & p(Y_k^r|x_{k-b+1:k}^r) \\ &= \prod_{j=1}^{J}\Big\{\bar{\alpha}^{r,j}\Big(p_{\xi_k^{r,j}}(y_k^{r,B,j}-u_k^{r,j})(1-\Psi_{\omega_k^{r,j}}(\tau^{r,j}-f^{r,j}(x_k^r))) \\ &\quad + p_{\xi_k^{r,j}}(y_k^{r,B,j}+u_k^{r,j})\Psi_{\omega_k^{r,j}}(\tau^{r,j}-f^{r,j}(x_k^r))\Big) \\ &\quad + (1-\bar{\alpha}^{r,j})p_{\xi_k^{r,j}}(y_k^{r,B,j})\Big\}. \end{aligned} \tag{22}$$

In what follows, we set out to derive the specific expression for $p(y_k^{r,I}|x_{k-b+1:k}^r)$. Recalling the models (5) and (6) related to the slow-rate integral measurements, along with the corresponding transmission models (7) and (9), we can acquire that if the condition $\mathrm{mod}(k-1,b)=0$ holds, the likelihood function can be expressed as:

$$\begin{aligned} & p(y_k^{r,I}|x_{k-b+1:k}^r) \\ &= p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=1)\Pr\{\beta_k^r=1\} \\ &\quad + p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=0)\Pr\{\beta_k^r=0\} \\ &= \bar{\beta}^r p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=1) \\ &\quad + (1-\bar{\beta}^r)p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=0). \end{aligned} \tag{23}$$

Note that the term $p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=1)$ can be rewritten by

$$\begin{aligned} & p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=1) \\ &= \int p(y_k^{r,I},\tilde{y}_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=1)\mathrm{d}\tilde{y}_k^{r,I} \\ &= \int p(y_k^{r,I}|\tilde{y}_k^{r,I},\beta_k^r=1)p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^r)\mathrm{d}\tilde{y}_k^{r,I} \end{aligned} \tag{24}$$

in which the following two facts have been harnessed:

$$\begin{aligned} & p(y_k^{r,I}|\tilde{y}_k^{r,I},x_{k-b+1:k}^r,\beta_k^r=1) = p(y_k^{r,I}|\tilde{y}_k^{r,I},\beta_k^r=1), \\ & p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=1) = p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^r). \end{aligned}$$

It should be pointed out that, in most cases, it is quite challenging (if not infeasible) to derive a closed-form expression for (24). To improve the generality of the proposed algorithm, we seek an approximate yet computable solution by resorting to the Monte Carlo approach. Specifically, we approximate the likelihood function by generating a sufficient number of samples from the distribution and averaging the results, i.e.,

$$\begin{aligned} & p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=1) \\ &\approx \frac{1}{N_1}\sum_{n=1}^{N_1} p(y_k^{r,I}|\tilde{y}_k^{r,I,\{n\}},\beta_k^r=1) \\ &= \frac{1}{N_1}\sum_{n=1}^{N_1} p_{\chi_k^r}(y_k^{r,I}-v_k^r\tilde{y}_k^{r,I,\{n\}}) \end{aligned} \tag{25}$$

where $\tilde{y}_k^{r,I,\{n\}} \sim p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^r)$ for $n=1,2,\ldots,N_1$. Notably, such a sampling process is dependent on the measurement models characterized by (5) and (6).

For the second term $p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=0)$, it is apparent that

$$p(y_k^{r,I}|x_{k-b+1:k}^r,\beta_k^r=0) = p_{\chi_k^r}(y_k^{r,I}). \tag{26}$$

Accordingly, the likelihood function with respect to the slow-rate integral measurement can be specified by

$$\begin{aligned} & p(y_k^{r,I}|x_{k-b+1:k}^r) \\ &\approx \frac{\bar{\beta}^r}{N_1}\sum_{n=1}^{N_1} p_{\chi_k^r}(y_k^{r,I}-v_k^r\tilde{y}_k^{r,I,\{n\}}) + (1-\bar{\beta}^r)p_{\chi_k^r}(y_k^{r,I}). \end{aligned} \tag{27}$$

Based on the above derivations, the importance weight for the l-th particle candidate associated with the r-th node under the deterministic channel gains can be approximately calculated by

$$w_k^{r,\{l\}} = \begin{cases} \Delta w_{k,2}^{r,\{l\}} w_{k-1}^{r,\{l\}} & \text{if } \mathrm{mod}(k-1,b)=0; \\ \Delta w_{k,1}^{r,\{l\}} w_{k-1}^{r,\{l\}} & \text{otherwise} \end{cases} \tag{28}$$

where $\Delta w_{k,1}^{r,\{l\}}$ and $\Delta w_{k,2}^{r,\{l\}}$ are defined as

$$\begin{aligned} & \Delta w_{k,1}^{r,\{l\}} \\ &= \prod_{j=1}^{J}\Big\{\bar{\alpha}^{r,j}\Big(p_{\xi_k^{r,j}}(y_k^{r,B,j}-u_k^{r,j})(1-\Psi_{\omega_k^{r,j}}(\tau^{r,j} \\ &\quad - f^{r,j}(x_k^{r,\{l\}}))) + p_{\xi_k^{r,j}}(y_k^{r,B,j}+u_k^{r,j})\Psi_{\omega_k^{r,j}}(\tau^{r,j} \\ &\quad - f^{r,j}(x_k^{r,\{l\}}))\Big) + (1-\bar{\alpha}^{r,j})p_{\xi_k^{r,j}}(y_k^{r,B,j})\Big\}, \end{aligned}$$

Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

and

$$\Delta w_{k,2}^{r,\{l\}} = \Delta w_{k,1}^{r,\{l\}} \Big[\frac{\bar{\beta}^r}{N_1}\sum_{n=1}^{N_1} p_{\chi_k^r}(y_k^{r,I} - v_k^r \tilde{y}_k^{r,I,\{l,n\}}) + (1-\bar{\beta}^r)p_{\chi_k^r}(y_k^{r,I})\Big]$$

with $\tilde{y}_k^{r,I,\{l,n\}} \sim p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^{r,\{l\}})$ for $n = 1,2,\ldots,N_1$.

Up to this point, the design process for the particle filtering scheme has been presented for nonlinear and non-Gaussian complex networks, accounting for the joint effects of deterministic channel gains, potential transmission failures, and multi-rate measurements. Next, we proceed to develop the corresponding filtering scheme for the case where the channel gains are stochastic.

B. Particle Filtering Scheme with Stochastic Channel Gains

In this subsection, we shall consider the multi-sensor particle filtering problem under the stochastic channel gains. More specifically, $u_k^{r,j}$ and $v_{t_i}^r$ in transmission model (7), characterizing the channel gains, are random variables and satisfy certain PDFs $p_{u_k^{r,j}}(\cdot)$ and $p_{v_{t_i}^r}(\cdot)$. The primary task remains to establish an explicit expression for the likelihood function tailored to the scenario of stochastic channel gains.

To begin with, let us consider the terms $p(y_k^{r,B,j}|x_k^r, \alpha_k^{r,j} = 1, \tilde{y}_k^{r,B,j} = 1)$ in (20). Based on the independence assumption of the random variables involved, it follows that:

$$\begin{aligned} &p(y_k^{r,B,j}|x_k^r, \alpha_k^{r,j} = 1, \tilde{y}_k^{r,B,j} = 1) \\ =& \int p_{\xi_k^{r,j}}(y_k^{r,B,j} - u_k^{r,j})p(u_k^{r,j})\mathrm{d}u_k^{r,j} \\ \approx& \frac{1}{M_1}\sum_{m=1}^{M_1} p_{\xi_k^{r,j}}(y_k^{r,B,j} - u_k^{r,j,\{m\}}) \end{aligned} \tag{29}$$

where the approximation is due to the use of the Monte Carlo technique, and the samples $u_k^{r,j,\{m\}} \sim p(u_k^{r,j})$ for $m = 1,2,\ldots,M_1$.

By the same token, another term $p(y_k^{r,B,j}|x_k^r, \alpha_k^{r,j} = 1, \tilde{y}_k^{r,B,j} = -1)$ in (20) can be rewritten as follows:

$$\begin{aligned} &p(y_k^{r,B,j}|x_k^r, \alpha_k^{r,j} = 1, \tilde{y}_k^{r,B,j} = -1) \\ \approx& \frac{1}{M_1}\sum_{m=1}^{M_1} p_{\xi_k^{r,j}}(y_k^{r,B,j} + u_k^{r,j,\{m\}}). \end{aligned} \tag{30}$$

Subsequently, let us consider the slow-rate integral measurements and proceed to the term $p(y_k^{r,I}|x_{k-b+1:k}^r, \beta_k^r = 1)$ in (23). It is not difficult to obtain that

$$\begin{aligned} &p(y_k^{r,I}|x_{k-b+1:k}^r, \beta_k^r = 1) \\ =& \iint p(y_k^{r,I}, \tilde{y}_k^{r,I}, v_k^r|x_{k-b+1:k}^r, \beta_k^r = 1)\mathrm{d}\tilde{y}_k^{r,I}\mathrm{d}v_k^r \\ =& \iint p(y_k^{r,I}|\tilde{y}_k^{r,I}, v_k^r, \beta_k^r = 1)p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^r)p(v_k^r)\mathrm{d}\tilde{y}_k^{r,I}\mathrm{d}v_k^r \\ \approx& \frac{1}{M_2N_2}\sum_{m=1}^{M_2}\sum_{n=1}^{N_2} p(y_k^{r,I}|\tilde{y}_k^{r,I,\{n\}}, v_k^{r,\{m\}}, \beta_k^r = 1) \\ =& \frac{1}{M_2N_2}\sum_{m=1}^{M_2}\sum_{n=1}^{N_2} p_{\chi_k^r}(y_k^{r,I} - v_k^{r,\{m\}}\tilde{y}_k^{r,I,\{n\}}) \end{aligned} \tag{31}$$

where $v_k^{r,\{m\}} \sim p(v_k^r)$ for $m = 1,2,\ldots,M_2$ and $\tilde{y}_k^{r,I,\{n\}} \sim p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^r)$ for $n = 1,2,\ldots,N_2$.

Now, we are in a position to determine the update rule of importance weights. More specifically, for the r-th node, the importance weight corresponding to the l-th particle candidate under the stochastic channel gains can be approximately computed by

$$w_k^{r,\{l\}} = \begin{cases} \Delta w_{k,2}^{r,\{l\}} w_{k-1}^{r,\{l\}} & \text{if } \mathrm{mod}(k-1,b) = 0; \\ \Delta w_{k,1}^{r,\{l\}} w_{k-1}^{r,\{l\}} & \text{otherwise} \end{cases} \tag{32}$$

where $\Delta w_{k,1}^{r,\{l\}}$ and $\Delta w_{k,2}^{r,\{l\}}$ are defined as

$$\begin{aligned} &\Delta w_{k,1}^{r,\{l\}} \\ =& \prod_{j=1}^{J}\Big\{\bar{\alpha}^{r,j}\Big(\big(\frac{1}{M_1}\sum_{m=1}^{M_1} p_{\xi_k^{r,j}}(y_k^{r,B,j} - u_k^{r,j,\{m\}})\big) \\ &\times (1 - \Psi_{\omega_k^{r,j}}(\tau^{r,j} - f^{r,j}(x_k^{r,\{l\}})))) + \big(\frac{1}{M_1}\sum_{m=1}^{M_1} p_{\xi_k^{r,j}}(y_k^{r,B,j} \\ &+ u_k^{r,j,\{m\}})\big)\Psi_{\omega_k^{r,j}}(\tau^{r,j} - f^{r,j}(x_k^{r,\{l\}}))\Big) \\ &+ (1-\bar{\alpha}^{r,j})p_{\xi_k^{r,j}}(y_k^{r,B,j})\Big\}, \end{aligned}$$

and

$$\begin{aligned} \Delta w_{k,2}^{r,\{l\}} = \Delta w_{k,1}^{r,\{l\}} \Big[&\frac{\bar{\beta}^r}{M_2N_2}\sum_{m=1}^{M_2}\sum_{n=1}^{N_2} p_{\chi_k^r}(y_k^{r,I} - v_k^{r,\{m\}} \\ &\times \tilde{y}_k^{r,I,\{l,n\}}) + (1-\bar{\beta}^r)p_{\chi_k^r}(y_k^{r,I})\Big] \end{aligned}$$

with $\tilde{y}_k^{r,I,\{l,n\}} \sim p(\tilde{y}_k^{r,I}|x_{k-b+1:k}^{r,\{l\}})$ for $n = 1,2,\ldots,N_2$.

C. Channel-Related Particle Filtering Algorithm

In this subsection, the detailed steps of the proposed particle filtering scheme are outlined in Algorithm 1 and the corresponding flowchart is displayed in Fig. 2 to facilitate the implementation.

Remark 1: It can be observed from the measurement models (5) and (6) that, if the matrix $H_{t_i}^r$ is identity matrix and other matrices H_s^r $(s = t_{i-1}+1,\ldots,t_i-1)$ are set to zero matrices, then the integral measurement models degenerate into regular measurement models. In other words, the results obtained in this paper are also applicable to the filtering problem that involves binary measurements and regular measurements sampled at different rates.

Remark 2: It should be emphasized that the state estimation problem considered in this paper is highly comprehensive since it embraces the general system nonlinearities, randomly switching couplings, non-Gaussian noises, multi-rate heterogeneous measurements, and channel-induced impairments. The joint impact of these engineering-oriented complexities renders it really challenging (if not impossible) to design the filter by employing the common approaches such as the linearization-based extended Kalman filtering technique and the H_∞ filtering method. In this sense, the proposed particle filtering scheme offers an effective method that complements the existing approaches for addressing the state estimation problem of certain complex networks.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

Algorithm 1 Channel-related particle filtering algorithm with multi-rate heterogeneous measurements.

Step 1. Particle initialization
For the r-th node, draw the initial particles $x_0^{r,\{l\}}$, $l = 1,2,\ldots,L$ from the density $p(x_0^r)$. Then, set the associated importance weights $w_0^{r,\{l\}}$, $l = 1,2,\ldots,L$ to be $\frac{1}{L}$ and the maximum recursive time instant K.

Step 2. Multi-rate measurement collection
At time instant k, collect both the fast-rate binary measurements $y_k^{r,B,j}$, $j = 1,2,\ldots,J$ and the slow-rate integral measurements $y_k^{r,I}$ transmitted over the imperfect channels if the condition $\mathrm{mod}(k-1,b) = 0$ is satisfied. Otherwise, collect only the fast-rate binary measurements.

Step 3. Particle propagation
Draw new particle $x_k^{r,\{l\}}$ from the mixture distribution characterized by (15) for $l = 1,2,\ldots,L$.

Step 4. Importance weight update
Allocate the unnormalized weights $\tilde{w}_k^{r,\{l\}}$, $l = 1,2,\ldots,L$ according to

$$\tilde{w}_k^{r,\{l\}} = \begin{cases} \Delta w_{k,2}^{r,\{l\}} w_{k-1}^{r,\{l\}} & \text{if } \mathrm{mod}(k-1,b)=0; \\ \Delta w_{k,1}^{r,\{l\}} w_{k-1}^{r,\{l\}} & \text{otherwise} \end{cases}$$

where the terms $\Delta w_{k,1}^{r,\{l\}}$ and $\Delta w_{k,2}^{r,\{l\}}$ are specified by (28) if the transmission channels are subject to deterministic gains, and (32) otherwise.

Step 5. Weight normalization
Calculate the normalized importance weights by $w_k^{r,\{l\}} = \tilde{w}_k^{r,\{l\}} / (\sum_{n=1}^{L} \tilde{w}_k^{r,\{n\}})$, $l = 1,2,\ldots,L$.

Step 6. State estimate update
Update the state estimate $\hat{x}_k^r$ by

$$\hat{x}_k^r = \sum_{l=1}^{L} w_k^{r,\{l\}} x_k^{r,\{l\}}.$$

Step 7. Resampling
Conduct the resampling procedure if the effective sample size is lower than a given threshold.

Step 8. If $k < K$, then assign $k = k+1$ and go to *Step 2*; otherwise go to *Step 9*.

Step 9. Stop the recursion.

Remark 3: Up to now, the channel-related particle filtering framework has been established for nonlinear complex networks with multi-rate heterogeneous measurements. In comparison to the existing literature on state estimation (e.g., [25], [26], [55], [56]), the distinguishing features of this paper can be summarized as follows.

1) The problem under investigation is novel as it addresses generally nonlinear complex networks subject to non-Gaussian noises, randomly switching couplings, and multi-rate heterogeneous measurements, which has not been sufficiently explored in previous studies.
2) The available measurements, derived from practical engineering applications, consist of fast-rate binary measurements and slow-rate integral measurements, both of which are transmitted through imperfect and lossy channels, introducing further complexity.
3) Two types of importance weight updating rules have been developed, which account for both deterministic and stochastic channel gains, while also considering potential transmission failures. This dual approach provides a robust framework for handling various channel conditions.

The above features distinguish the proposed particle filtering approach from existing methods and contribute to its practical applicability and theoretical innovation.

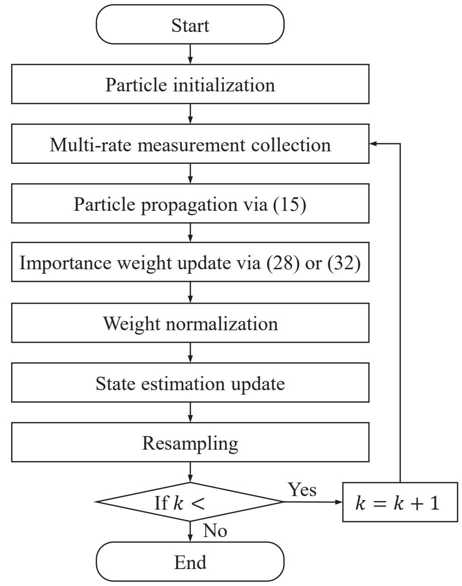


Fig. 2: Flowchart of Algorithm 1.

IV. Simulation Validations

In this section, we conduct numerical simulations to demonstrate the effectiveness of the established particle filtering algorithm for nonlinear complex networks.

Example 1: To begin with, consider a complex network described by equation (1), consisting of four coupled nodes, where the nonlinearities and parameters for the system are specified as follows:

$$g^1(x_k^1) = \begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.85 \end{bmatrix} x_k^1 + \begin{bmatrix} -0.5\tanh(0.1x_{k,1}^1) \\ -0.4\tanh(0.1x_{k,2}^1) \end{bmatrix},$$

$$g^2(x_k^2) = \begin{bmatrix} 0.85 & 0.2 \\ 0.1 & 0.9 \end{bmatrix} x_k^2 + \begin{bmatrix} -0.4\tanh(0.3x_{k,1}^2) \\ -0.5\tanh(0.2x_{k,2}^2) \end{bmatrix},$$

$$g^3(x_k^3) = \begin{bmatrix} 0.75 & 0.2 \\ 0.15 & 0.8 \end{bmatrix} x_k^3 + \begin{bmatrix} 0.1\tanh(0.2x_{k,1}^3) \\ 0.2\tanh(0.2x_{k,2}^3) \end{bmatrix},$$

$$g^4(x_k^4) = \begin{bmatrix} 0.72 & 0.1 \\ 0.3 & 0.8 \end{bmatrix} x_k^4 + \begin{bmatrix} 0.3\tanh(0.3x_{k,1}^4) \\ 0.2\tanh(0.4x_{k,2}^4) \end{bmatrix},$$

$$\Theta_0 = \begin{bmatrix} -0.3 & 0.1 & 0.1 & 0.1 \\ 0.1 & -0.3 & 0.1 & 0.1 \\ 0.1 & 0.1 & -0.3 & 0.1 \\ 0.1 & 0.1 & 0.1 & -0.3 \end{bmatrix}, \ \Lambda_0 = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix},$$

$$\Theta_1 = \begin{bmatrix} -0.6 & 0.2 & 0.2 & 0.2 \\ 0.1 & -0.2 & 0.05 & 0.05 \\ 0.1 & 0.2 & -0.4 & 0.1 \\ 0.1 & 0.05 & 0.15 & -0.3 \end{bmatrix}, \ \Lambda_1 = \begin{bmatrix} 0.6 & 0 \\ 0 & 0.4 \end{bmatrix},$$

and $p_{\eta,0} = 0.8$. The process noises μ_k^r are portrayed by the Gaussian mixture models, i.e.,

$$p(\mu_k^r) = (1-\rho^r)\mathcal{N}(\mu_k^r; \bar{\mu}_1^r, \Sigma_{\mu,1}^r) + \rho^r \mathcal{N}(\mu_k^r; \bar{\mu}_2^r, \Sigma_{\mu,2}^r) \quad (33)$$

where $\rho^r = 0.2$, $\bar{\mu}_1^r = [2\ 2]^T$, $\bar{\mu}_2^r = [2\ 2]^T$, $\Sigma_{\mu,1}^r = I$, and $\Sigma_{\mu,2}^r = 100I$.

For the fast-rate binary measurements with $J = 4$ and slow-rate integral measurements with $b = 10$, the corresponding parameters are summarized as follows:

$$f^{r,1}(x_k^r) = \sin(x_{k,1}^r) + \cos(x_{k,2}^r), \ f^{r,2}(x_k^r) = 2\sin(x_{k,1}^r),$$
$$f^{r,3}(x_k^r) = 2\cos(x_{k,2}^r), \ f^{r,4}(x_k^r) = \left|\sin(x_{k,1}^r) - \cos(x_{k,2}^r)\right|,$$
$$\tau^{r,j} = 0.5, \ H_s^r = \begin{bmatrix} 1 & 0 \\ 0 & 0.5 \end{bmatrix}, \ h^r(\breve{x}_{t_i}^r) = \begin{bmatrix} 0.6 & -0.4 \end{bmatrix} \breve{x}_{t_i}^r.$$

The measurement noises $\omega_k^{r,j}$ and $\nu_{t_i}^r$ obey, respectively, the Gaussian distribution and the Gaussian mixture distribution, i.e.,

$$p(\omega_k^{r,j}) = \mathcal{N}(\omega_k^{r,j}; \bar{\omega}^{r,j}, \Sigma_\omega^{r,j}),$$
$$p(\nu_{t_i}^r) = (1-\kappa_1^r)\mathcal{N}(\nu_{t_i}^r; \bar{\nu}_1^r, \Sigma_{\nu,1}^r) + \kappa_1^r \mathcal{N}(\nu_{t_i}^r; \bar{\nu}_2^r, \Sigma_{\nu,2}^r)$$

where $\kappa_1^r = 0.4$, $\bar{\omega}^{r,j} = 0$, $\Sigma_\omega^{r,j} = 0.04$, $\bar{\nu}_1^r = -10$, $\Sigma_{\nu,1}^r = 1$, $\bar{\nu}_2^r = 10$, and $\Sigma_{\nu,2}^r = 100$.

The channel noises $\xi_k^{r,j}$ and $\chi_{t_i}^r$ are both depicted by the Gaussian mixture models, i.e.,

$$p(\xi_k^{r,j}) = (1-\kappa_2^{r,j})\mathcal{N}(\xi_k^{r,j}; \bar{\xi}_1^{r,j}, \Sigma_{\xi,1}^{r,j}) + \kappa_2^{r,j} \mathcal{N}(\xi_k^{r,j}; \bar{\xi}_2^{r,j}, \Sigma_{\xi,2}^{r,j}),$$
$$p(\chi_{t_i}^r) = (1-\kappa_3^r)\mathcal{N}(\chi_{t_i}^r; \bar{\chi}_1^r, \Sigma_{\chi,1}^r) + \kappa_3^r \mathcal{N}(\chi_{t_i}^r; \bar{\chi}_2^r, \Sigma_{\chi,2}^r)$$

where $\kappa_2^{r,j} = 0.2$, $\kappa_3^r = 0.4$, $\bar{\xi}_1^{r,j} = 0$, $\Sigma_{\xi,1}^{r,j} = 1$, $\bar{\xi}_2^{r,j} = 0$, $\Sigma_{\xi,2}^{r,j} = 4$, $\bar{\chi}_1^r = -10$, $\Sigma_{\chi,1}^r = 1$, $\bar{\chi}_2^r = 10$, and $\Sigma_{\chi,2}^r = 100$. In addition, the parameters related to the phenomenon of packet dropouts are set as $\bar{\alpha}^{r,j} = 0.7$ and $\bar{\beta}^r = 0.7$.

With the aim of statistically evaluating the performance of the developed filtering scheme, we employ the root mean-square error (RMSE) index as follows:

$$\mathrm{RMSE}_k^r = \sqrt{\frac{1}{N_m}\sum_{i=1}^{N_m}\left[(x_{k,1}^{r,i} - \hat{x}_{k,1}^{r,i})^2 + (x_{k,2}^{r,i} - \hat{x}_{k,2}^{r,i})^2\right]}$$

where N_m represents the number of independent Monte Carlo runs. $x_{k,1}^{r,i}$ and $x_{k,2}^{r,i}$ are, respectively, the first and the second state components of the r-th node at time instant k in the i-th Monte Carlo run, and their estimates are denoted by $\hat{x}_{k,1}^{r,i}$ and $\hat{x}_{k,2}^{r,i}$.

First of all, we consider the case of deterministic channel gains. Specifically, we set $u_k^{r,j} = 0.8$, $v_{t_i}^r = 0.8$, $N_1 = 10$, and $L = 500$. In the simulations, the proposed channel-related multi-sensor particle filtering algorithm (abbreviated as MPF-D) will be compared with the following two filtering algorithms under deterministic channel gains: 1) MPF-I: the multi-sensor particle filtering algorithm neglecting the effect of packet dropouts; and 2) MPF-II: the multi-sensor particle filtering algorithm neglecting the effect of randomly switching couplings.

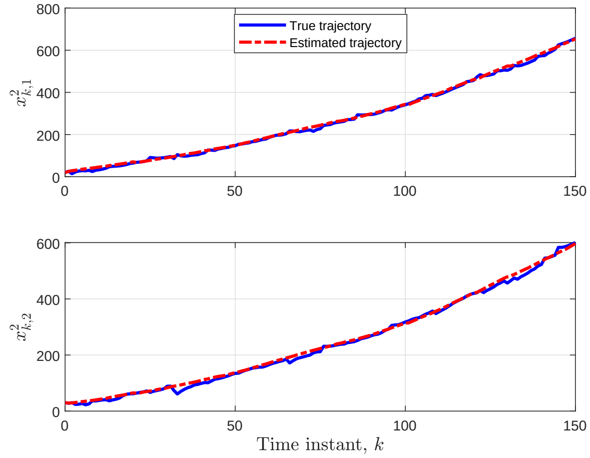


Fig. 3: The true and estimated trajectories of the second node.

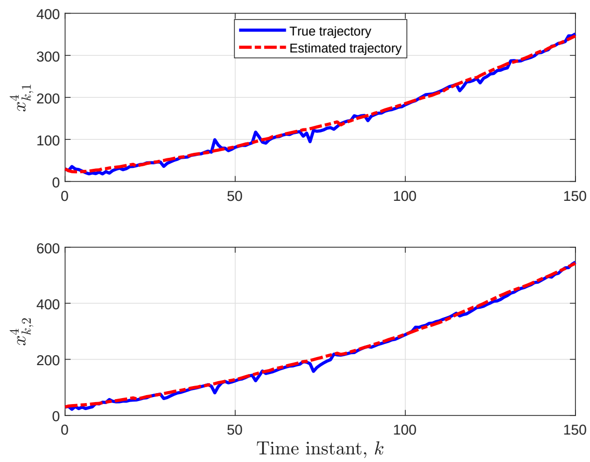


Fig. 4: The true and estimated trajectories of the fourth node.

One realization of the true state trajectories and their respective estimates is shown in Figs. 3-4, where, for the sake of brevity, only the simulation results for the second and fourth nodes are presented. It can be observed from these figures that the proposed filtering algorithm effectively tracks the true state trajectories, demonstrating its capability in handling nonlinearities and uncertainties within the system. Fig. 5 illustrates the raw measurements and the received measurements (those available to the remote filter) over the first 70 time instants for the fourth node. It is notable that transmission over imperfect channels results in distortion of the raw measurements, and this highlights the challenges posed by channel imperfections, such as packet loss and signal fading, which the filtering algorithm successfully mitigates, providing reliable state estimates despite these conditions.

The RMSE trajectories of different filtering algorithms, calculated over 100 Monte Carlo runs, are depicted in Figs. 6-7, from which we can conclude that the tracking performance of the proposed MPF-D algorithm is superior to that of other two

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

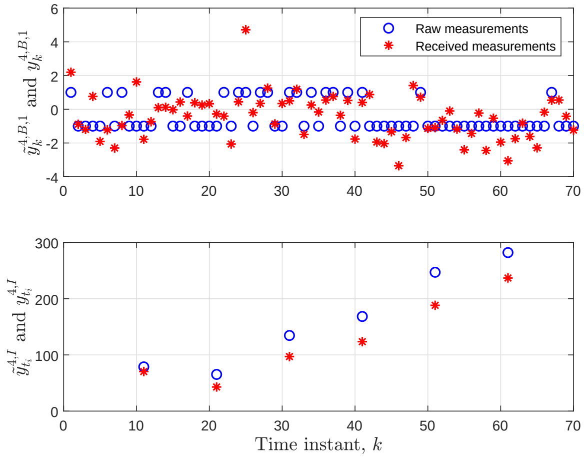


Fig. 5: The raw and received measurements for the fourth node.

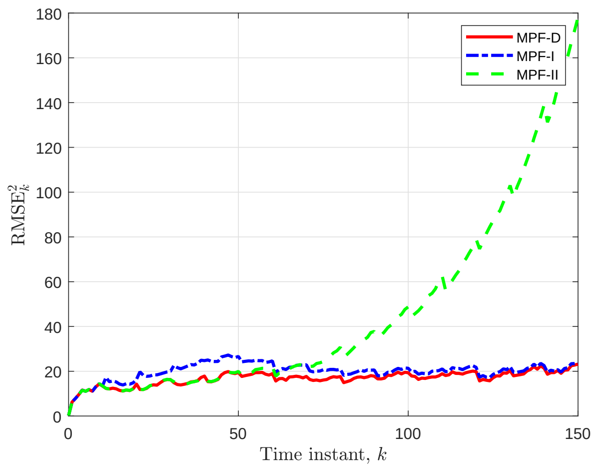


Fig. 6: The RMSEs of different algorithms for the second node.

filtering algorithms. In order to explore the effects of different packet arrival rates and different sampling periods of integral measurements, further simulation results are delineated in Figs. 8-11, where only the parameter of interest varies. It is obvious from Figs. 8-9 that the lower packet arrival rate would give rise to larger performance degradation. As can be observed from Figs. 10-11, the increase of sampling period generally contributes to the decrease of tracking accuracy.

In what follows, let us move on to the scenario with stochastic channel gains. In this case, the channel gains $u_k^{r,j}$ and $v_{t_i}^r$ are all assumed to obey the Rayleigh distribution with scale parameter set as 0.6. Moreover, $N_2 = 10$ and $M_1 = M_2 = 10$. Other parameters are the same as those in the deterministic scenario. One realization of the true state trajectories and the corresponding estimates obtained by the proposed algorithm are summarized in Figs. 12-13, which indicate that the proposed filtering scheme is also effective when it comes to the stochastic channel gains. Fig. 14 displays the partial raw measurements and the received measurements for the fourth node, and Fig. 15 portrays the realizations of stochastic channel gains $u_k^{4,1}$ using the normalized histogram.

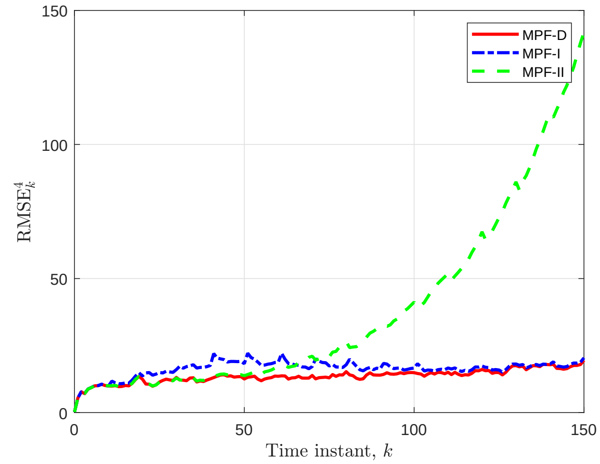


Fig. 7: The RMSEs of different algorithms for the fourth node.

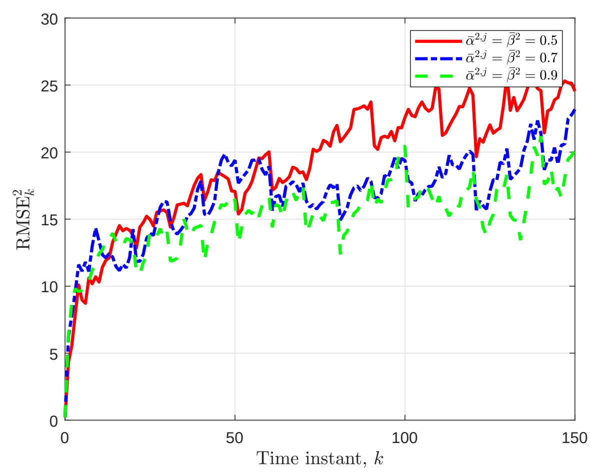


Fig. 8: The RMSEs of different packet arrival rates for the second node.

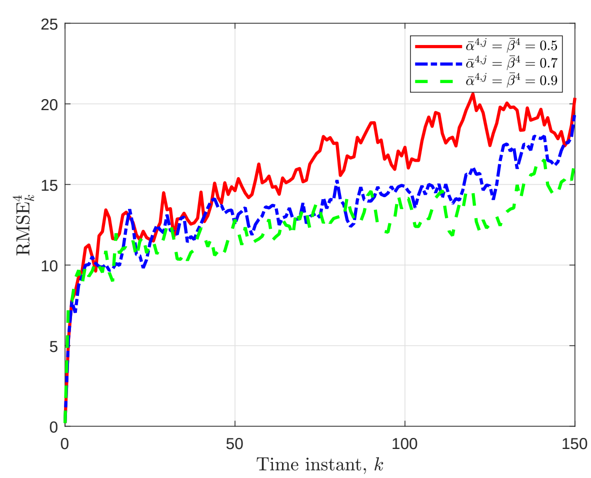


Fig. 9: The RMSEs of different packet arrival rates for the fourth node.

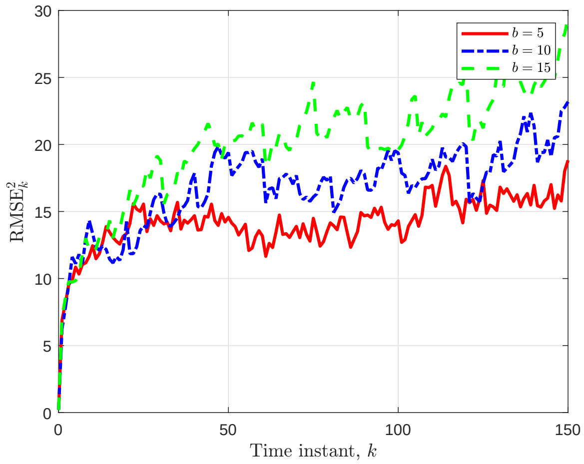


Fig. 10: The RMSEs of different sampling periods for the second node.

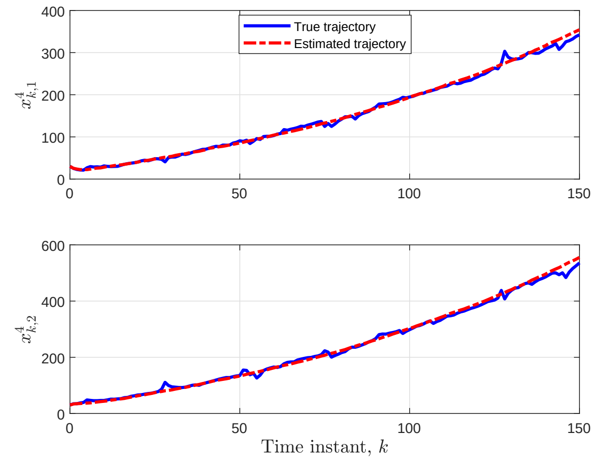


Fig. 13: The true and estimated trajectories of the fourth node.

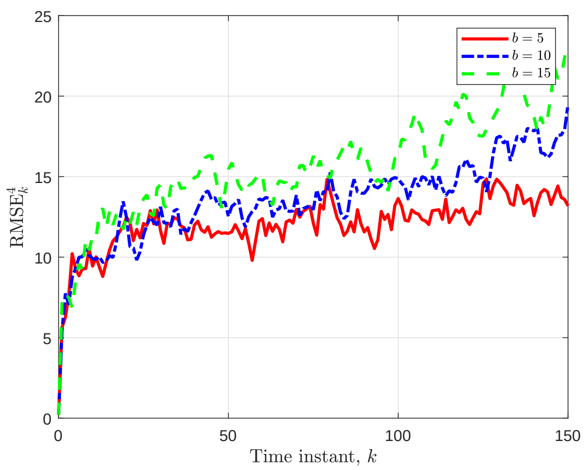


Fig. 11: The RMSEs of different sampling periods for the fourth node.

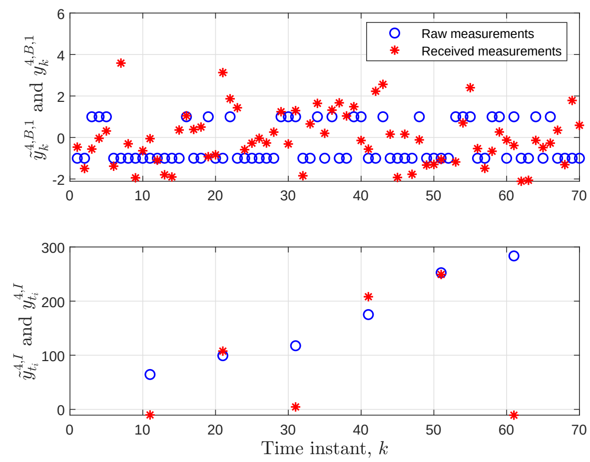


Fig. 14: The raw and received measurements for the fourth node.

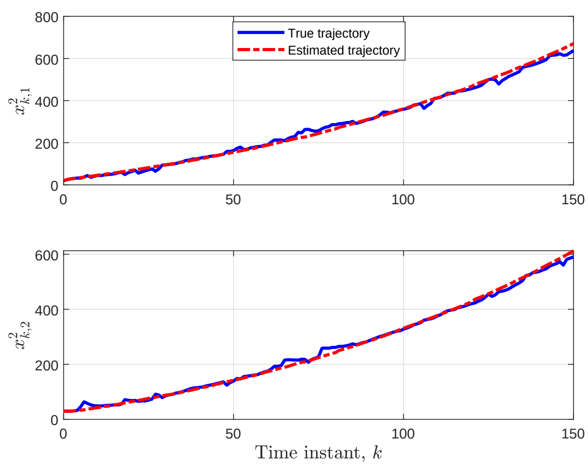


Fig. 12: The true and estimated trajectories of the second node.

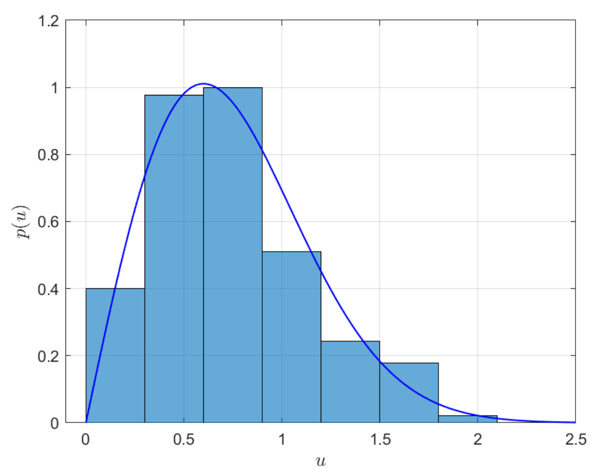


Fig. 15: Normalized histogram of the stochastic channel gains with regard to the first binary sensor for the fourth node. The blue curve depicts the PDF of Rayleigh distribution with scale parameter 0.6.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

The simulation results over 100 Monte Carlo runs are summarized in Table I, where MPF-S denotes the proposed filtering algorithm for stochastic channel gains; MPF-I and MPF-II stand for the aforementioned algorithms with adaptation to stochastic channel gains; and $\overline{\mathrm{RMSE}}^i$ represents the average RMSE for the i-th node. It is clear from Table I that the proposed MPF-S exhibits the best tracking performance as expected in comparison with other two algorithms, which again testifies the superiority of our developed scheme. Subsequently, we conduct further simulations to probe the effect of the number of M_1 and M_2, and the corresponding results in terms of average RMSE over all nodes and average running time are listed in Table II. From Table II, we are able to see that the increased number of samples would improve the filtering performance but at the sacrifice of computational efficiency. As such, an appropriate number of samples should be chosen in practice to attain a balance between the computational efficiency and filtering performance.

TABLE I: Performance comparisons with different filtering algorithms.

Algorithms	MPF-S	MPF-I	MPF-II
$\overline{\mathrm{RMSE}}^1$	51.0568	53.2974	156.0206
$\overline{\mathrm{RMSE}}^2$	37.6584	39.2410	92.5426
$\overline{\mathrm{RMSE}}^3$	28.0477	29.1529	68.6377
$\overline{\mathrm{RMSE}}^4$	28.2669	29.2971	72.3249

TABLE II: Performance comparisons with different numbers of M_1 and M_2.

$M_1,\ M_2$	20	35	50
Average RMSE	35.0216	34.5219	32.3051
Average running time (s)	0.0961	0.1066	0.1169

Example 2: In this example, let us consider a practical localization problem involving three mobile robots (i.e., $S = 3$), and the dynamics of the r-th mobile robot can be described by [25]:

$$x_{k+1}^r = x_k^r + \begin{bmatrix} v_k^r \cos x_{k,\phi}^r \\ v_k^r \sin x_{k,\phi}^r \\ \sigma_k^r \end{bmatrix} + (1-\eta_k)\sum_{s=1}^{3}\theta_0^{rs}\Lambda_0 x_k^s + \eta_k \sum_{s=1}^{3}\theta_1^{rs}\Lambda_1 x_k^s + \mu_k^r$$

where $x_k^r = \begin{bmatrix} x_{k,e}^r & x_{k,n}^r & x_{k,\phi}^r \end{bmatrix}^T$ with $(x_{k,e}^r, x_{k,n}^r)$ and $x_{k,\phi}^r$ being the position and the orientation of the r-th mobile robot at time instant k, respectively. Moreover, v_k^r and σ_k^r signify, respectively, the corresponding velocity and angular velocity. In the simulations, v_k^r and σ_k^r are, respectively, set as 0.5 and 0.32, and $p_{\eta,0} = 0.5$. The process noise μ_k^r is of the form (33) with parameters $\rho^r = 0.2$, $\bar{\mu}_1^r = \bar{\mu}_2^r = [0\ 0\ 0]^T$, $\Sigma_{\mu,1}^r = 0.01^2 I$, and $\Sigma_{\mu,2}^r = 0.01I$. Other parameters are set as follows:

$$\Theta_0 = \begin{bmatrix} -0.2 & 0.1 & 0.1 \\ 0.1 & -0.2 & 0.1 \\ 0.1 & 0.1 & -0.2 \end{bmatrix}, \ \Lambda_0 = 0.05I,$$

$$\Theta_1 = \begin{bmatrix} -0.6 & 0.4 & 0.2 \\ 0.3 & -0.4 & 0.1 \\ 0.2 & 0.3 & -0.5 \end{bmatrix}, \ \Lambda_1 = 0.5I.$$

For the fast-rate binary measurements with $J = 4$ and slow-rate integral measurements with $b = 3$, the corresponding parameters are given by

$$\begin{aligned} &f^{r,1}(x_k^r) = (x_{k,e}^r)^2 + (x_{k,n}^r)^2, \\ &f^{r,2}(x_k^r) = (x_{k,e}^r - 10)^2 + (x_{k,n}^r)^2, \\ &f^{r,3}(x_k^r) = (x_{k,e}^r)^2 + (x_{k,n}^r - 10)^2, \\ &f^{r,4}(x_k^r) = (x_{k,e}^r - 10)^2 + (x_{k,n}^r - 10)^2, \ \tau^{r,j} = 50, \\ &H_{t_{i-1}+1}^r = \mathrm{diag}\{-1,-1,0\}, \ H_{t_{i-1}+2}^r = \mathrm{diag}\{0,0,0\}, \\ &H_{t_i}^r = \mathrm{diag}\{1,1,0\}, \ h^r(\breve{x}_{t_i}^r) = \frac{1}{2}\sqrt{(\breve{x}_{t_i,1}^r)^2 + (\breve{x}_{t_i,2}^r)^2}. \end{aligned}$$

Similar to the case in *Example 1*, the measurement noises $\omega_k^{r,j}$ and $\nu_{t_i}^r$ obey, respectively, the Gaussian distribution and the Gaussian mixture distribution with parameters $\kappa_1^r = 0.2$, $\bar{\omega}^{r,j} = 0$, $\Sigma_\omega^{r,j} = 0.04$, $\bar{\nu}_1^r = \bar{\nu}_2^r = 0$, $\Sigma_{\nu,1}^r = 0.01$, and $\Sigma_{\nu,2}^r = 0.04$. Moreover, the parameters of the channel noises $\xi_k^{r,j}$ and $\chi_{t_i}^r$ are specified by $\kappa_2^{r,j} = 0.2$, $\kappa_3^r = 0.4$, $\bar{\xi}_1^{r,j} = \bar{\xi}_2^{r,j} = 0$, $\Sigma_{\xi,1}^{r,j} = 0.01$, $\Sigma_{\xi,2}^{r,j} = 0.04$, $\bar{\chi}_1^r = \bar{\chi}_2^r = 0$, $\Sigma_{\chi,1}^r = 0.01$, and $\Sigma_{\chi,2}^r = 0.04$. In the simulations, $\bar{\alpha}^{r,j} = 0.6$, $\bar{\beta}^r = 0.6$, and the channel gains $u_k^{r,j}$ and $v_{t_i}^r$ obey the Rayleigh distribution with scale parameter set as 1.

The simulation results in one realization are displayed in Figs. 16-17, where the true and estimated trajectories of the first and third robots are depicted. Obviously, the proposed particle filtering algorithm is able to well track the trajectories of the mobile robots. To illustrate the superiority of the proposed algorithm, the RMSE behaviors of different algorithms (with the same abbreviations as in *Example 1*), calculated over 100 Monte Carlo runs, are shown in Figs. 18-19. It is clear that compared to the other two algorithms, the proposed MPF-S delivers superior tracking performance. These results further confirm the effectiveness of the proposed scheme.

V. Conclusions

In this paper, we have addressed the multi-sensor particle filtering problem for a class of nonlinear complex networks subject to non-Gaussian noises and randomly switching couplings. A set of Bernoulli-distributed random variables with known probability distributions has been used to model the random occurrence of switching couplings and packet dropouts. The filtering problem has incorporated both binary measurements and integral measurements with different sampling periods, which are transmitted over imperfect wireless communication channels and considered at the remote filter end. Using the Monte Carlo approximation technique and derived weight update rules, we have proposed two types of particle filtering algorithms, each tailored to the gain properties of the wireless channels (deterministic or stochastic). These

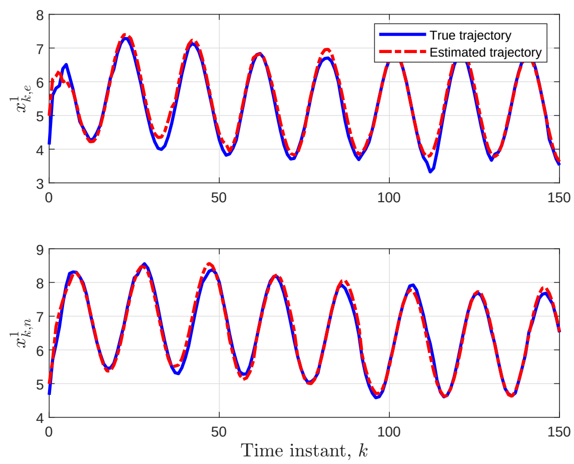


Fig. 16: The true and estimated trajectories of the first robot.

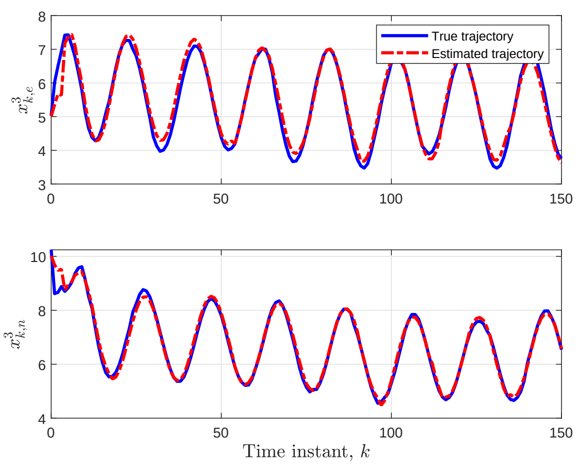


Fig. 17: The true and estimated trajectories of the third robot.

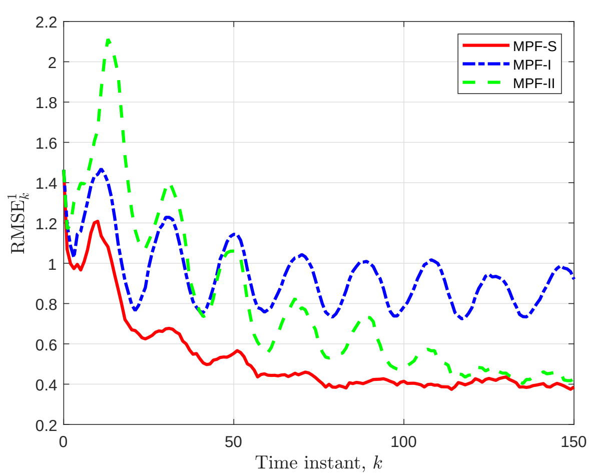


Fig. 18: The RMSEs of different algorithms for the first robot.

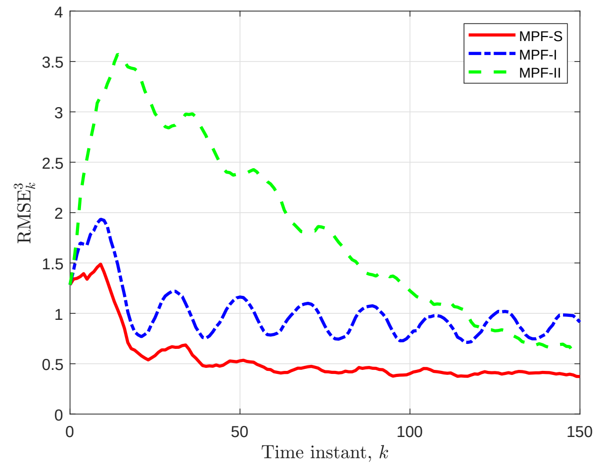


Fig. 19: The RMSEs of different algorithms for the third robot.

algorithms have been designed to handle the complexities of multi-rate heterogeneous measurements. Finally, a series of Monte Carlo simulations has been conducted, with performance comparisons, to verify the effectiveness and superiority of the proposed channel-related particle filtering algorithms. In the future, a promising yet difficult research topic is to conduct a rigorous performance analysis for the proposed algorithms.

REFERENCES

[1] G. A. Pagani and M. Aiello, The power grid as a complex network: A survey, *Physica A: Statistical Mechanics and its Applications*, vol. 392, no. 11, pp. 2688–2700, 2013.

[2] P. Gao, C. Jia and A. Zhou, Encryption-decryption-based state estimation for nonlinear complex networks subject to coupled perturbation, *Systems Science & Control Engineering*, vol. 12, no. 1, art. no. 2357796, 2024.

[3] Y. Wang, Q. Song and Y. Liu, Synchronisation of quaternion-valued neural networks with neutral delay and discrete delay via aperiodic intermittent control, *International Journal of Systems Science*, vol. 56, no. 7, pp. 1395–1412, 2025.

[4] A. Bombelli, B. F. Santos and L. Tavasszy, Analysis of the air cargo transport network using a complex network theory perspective, *Transportation Research Part E: Logistics and Transportation Review*, vol. 138, art. no. 101959, 2020.

[5] L. Zhao and B. Li, Adaptive fixed-time control for multiple switched coupled neural networks, *International Journal of Network Dynamics and Intelligence*, vol. 3, no. 3, art. no. 100018, 2024.

[6] L. Cao, W. Zhang and H. Guo, Finite-time cluster synchronisation of complex networks with multi-weights and nonlinear couplings via semi-intermittent control, *International Journal of Systems Science*, vol. 56, no. 11, pp. 2624–2638 , 2025.

[7] Y. Tang, F. Qian, H. Gao and J. Kurths, Synchronization in complex networks and its application – A survey of recent advances and challenges, *Annual Reviews in Control*, vol. 38, no. 2, pp. 184–198, 2014.

[8] C. Yang, J. Liang and W. Xu, PI observer-based synchronization control for singularly perturbed complex dynamical networks: An improved coding-decoding protocol scheme, *IEEE Transactions on Network Science and Engineering*, vol. 11, no. 1, pp. 858–871, 2024.

[9] Y. Guo, Z. Wang, J.-Y. Li and Y. Xu, Pinning synchronization for stochastic complex networks with randomly occurring nonlinearities: tackling bit rate constraints and allocations, *IEEE Transactions on Cybernetics*, vol. 54, no. 12, pp. 7248–7260, 2024.

[10] X. Yang, J. Lam, D. W. C. Ho and Z. Feng, Fixed-time synchronization of complex networks with impulsive effects via nonchattering control, *IEEE Transactions on Automatic Control*, vol. 62, no. 11, pp. 5511–5521, 2017.

[11] D. Zhao, C. Gao, J. Li, H. Fu and D. Ding, PID control and PI state estimation for complex networked systems: a survey, *International Journal of Systems Science*, vol. 56, no. 11, pp. 2735–2750, 2025.

[12] R. Zhang, H. Liu, Y. Liu and H. Tan, Dynamic event-triggered state estimation for discrete-time delayed switched neural networks with constrained bit rate, *Systems Science & Control Engineering*, vol. 12, no. 1, art. no. 2334304, 2024.

[13] Y. Xu, R. Lu, H. Peng, K. Xie and A. Xue, Asynchronous dissipative state estimation for stochastic complex networks with quantized jumping coupling and uncertain measurements, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 2, pp. 268–277, 2017.

[14] J. Hu, Z. Wang and G.-P. Liu, Delay compensation-based state estimation for time-varying complex networks with incomplete observations and dynamical bias, *IEEE Transactions on Cybernetics*, vol. 52, no. 11, pp. 12071–12083, 2022.

[15] C. Liu, Z. Wang, R. Lu, T. Huang and Y. Xu, Finite-time estimation for Markovian BAM neural networks with asymmetrical mode-dependent delays and inconstant measurements, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 1, pp. 344–354, 2023.

[16] H. Song, P. Shi, C.-C. Lim, W.-A. Zhang and L. Yu, Set-membership estimation for complex networks subject to linear and nonlinear bounded attacks, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 1, pp. 163–173, 2020.

[17] K. Zhang, S. Luo, H.-N. Wu and R. Su, Data-driven tracking control for non-affine yaw channel of helicopter via off-policy reinforcement learning, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 61, no. 3, pp. 7725–7737, 2025.

[18] I. Bilik and J. Tabrikian, MMSE-based filtering in presence of non-Gaussian system and measurement noise, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 46, no. 3, pp. 1153–1170, 2010.

[19] Y. Zhang, G. Liu and X. Song, Unscented recursive three-step filter based unbiased minimum-variance estimation for a class of nonlinear systems, *International Journal of Systems Science*, vol. 56, no. 2, pp. 227–236, 2025.

[20] H. Zhao, B. Tian and B. Chen, Robust stable iterated unscented Kalman filter based on maximum correntropy criterion, *Automatica*, vol. 142, art. no. 110410, 2022.

[21] X. Meng, H. Wang, Y. Li and Y. Shen, Unscented Kalman filtering for nonlinear systems with stochastic nonlinearities under FlexRay protocol, *International Journal of Network Dynamics and Intelligence*, vol. 4, no. 2, art. no. 100010, 2025.

[22] N. Yang, D. Chen, D. Ji and Z. Wu, Resilient state estimation for nonlinear complex networks with time-delay under stochastic communication protocol, *Neurocomputing*, vol. 346, pp. 38–47, 2019.

[23] Y. Chen, X. Meng, Z. Wang and H. Dong, Event-triggered recursive state estimation for stochastic complex dynamical networks under hybrid attacks, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 3, pp. 1465–1477, 2023.

[24] W. Li, Y. Jia and J. Du, Resilient filtering for nonlinear complex networks with multiplicative noise, *IEEE Transactions on Automatic Control*, vol. 64, no. 6, pp. 2522–2528, 2019.

[25] W. Li, Y. Jia and J. Du, State estimation for stochastic complex networks with switching topology, *IEEE Transactions on Automatic Control*, vol. 62, no. 12, pp. 6377–6384, 2017.

[26] H. Dong, N. Hou and Z. Wang, Fault estimation for complex networks with randomly varying topologies and stochastic inner couplings, *Automatica*, vol. 112, art. no. 108734, 2020.

[27] J. Fan, R. Jia, K. Zhang and J. Guo, Parameter identification of FIR systems with binary-valued observations: when the event-driven communication mechanism encounters DoS attacks, *International Journal of Systems Science*, vol. 56, no. 13, pp. 3156–3176, 2025.

[28] P. M. Djurić, M. Vemula and M. F. Bugallo, Target tracking by particle filtering in binary sensor networks, *IEEE Transactions on Signal Processing*, vol. 56, no. 6, pp. 2229–2238, 2008.

[29] Y. Zhao, L. Y. Wang, G. G. Yin and J.-F. Zhang, Identification of Wiener systems with binary-valued output observations, *Automatica*, vol. 43, no. 10, pp. 1752–1765, 2007.

[30] W. Song, Z. Wang, J. Wang, F. E. Alsaadi and J. Shan, Secure particle filtering for cyber-physical systems with binary sensors under multiple attacks, *IEEE Systems Journal*, vol. 16, no. 1, pp. 603–613, 2022.

[31] X. Yan, B. Chen and Z. Hu, Distributed estimation for interconnected dynamic systems under binary sensors, *IEEE Sensors Journal*, vol. 22, no. 13, pp. 13153–13161, 2022.

[32] Y.-B. Huang, Z. Wang, Y. He and M. Wu, Recursive state estimation for discrete-time nonlinear systems with binary sensors: a locally minimized variance approach, *IEEE Transactions on Automatic Control*, vol. 69, no. 9, pp. 6317–6324, 2024.

[33] G. Battistelli, L. Chisci and S. Gherardini, Moving horizon estimation for discrete-time linear systems with binary sensors: Algorithms and stability results, *Automatica*, vol. 85, pp. 374–385, 2017.

[34] M. Casini, A. Garulli and A. Vicino, Set membership state estimation for discrete-time linear systems with binary sensor measurements, *Automatica*, vol. 159, art. no. 111396, 2024.

[35] S. Cai and J. Liang, Recursive filtering for nonlinear systems with relay communication, energy harvesting and correlated noises, *International Journal of Network Dynamics and Intelligence*, vol. 4, no. 3, art. no. 100021, Sept. 2025.

[36] S. Liu, L. Wang, Y. Zhang, Y.-A. Wang and H. Dong, Recursive filtering of networked systems with communication protocol scheduling: a survey, *International Journal of Systems Science*, vol. 56, no. 11, pp. 2499–2516, 2025.

[37] R. Hostettler and P. M. Djurić, Vehicle tracking based on fusion of magnetometer and accelerometer sensor measurements with particle filtering, *IEEE Transactions on Vehicular Technology*, vol. 64, no. 11, pp. 4917–4928, 2015.

[38] B. Shen, X. Wang and L. Zou, Maximum correntropy Kalman filtering for non-Gaussian systems with state saturations and stochastic nonlinearities, *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 5, pp. 1223–1233, 2023.

[39] Y. Guo and B. Huang, State estimation incorporating infrequent, delayed and integral measurements, *Automatica*, vol. 58, pp. 32–38, 2015.

[40] N. Hou, J. Li, H. Liu, Y. Ge and H. Dong, Finite-horizon resilient state estimation for complex networks with integral measurements from partial nodes, *Science China Information Sciences*, vol. 65, art. no. 132205, 2022.

[41] A. Kheirandish, A. Fatehi and M. S. Gheibi, Identification of slow-rate integrated measurement systems using expectation-maximization algorithm, *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 12, pp. 9477–9484, 2020.

[42] A. Fatehi and B. Huang, State estimation and fusion in the presence of integrated measurement, *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 9, pp. 2490–2499, 2017.

[43] R. Han, Y. Salehi, B. Huang and V. Prasad, State estimation for multirate measurements in the presence of integral term and variable delay, *IEEE Transactions on Control Systems Technology*, vol. 29, no. 6, pp. 2416–2426, 2021.

[44] J. Baillieul and P. J. Antsaklis, Control and communication challenges in networked real-time systems, *Proceedings of the IEEE*, vol. 95, no. 1, pp. 9–28, 2007.

[45] W. Chen, J. Hu, Z. Wu and S. Ma, A survey on fault detection for networked systems under communication constraints, *Systems Science & Control Engineering*, vol. 13, no. 1, art. no. 2460434, 2025.

[46] R. Caballero-Águila and J. Linares-Pérez, Centralized fusion estimation in networked systems: addressing deception attacks and packet dropouts with a zero-order hold approach, *International Journal of Network Dynamics and Intelligence*, vol. 3, no. 4, art. no. 100021, 2024.

[47] L. Zou, Z. Wang, H. Dong, X. Yi and Q.-L. Han, Recursive filtering under probabilistic encoding-decoding schemes: handling randomly occurring measurement outliers, *IEEE Transactions on Cybernetics*, vol. 54, no. 6, pp. 3378–3391, 2024.

[48] X. Meng, Z. Wang, F. Wang and Y. Chen, Finite-horizon H_∞ state estimation for complex networks with uncertain couplings and packet losses: Handling amplify-and-forward relays, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 12, pp. 17493–17503, 2024.

[49] O. Ozdemir, R. Niu and P. K. Varshney, Channel aware target localization with quantized data in wireless sensor networks, *IEEE Transactions on Signal Processing*, vol. 57, no. 3, pp. 1190–1202, 2009.

[50] K. Zhang, R. Su, H. Zhang and Y. Tian, Adaptive resilient event-triggered control design of autonomous vehicles with an iterative single critic learning framework, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 12, pp. 5502–5511, 2021.

[51] X. Yang, R. Niu, E. Masazade and P. K. Varshney, Channel-aware tracking in multi-hop wireless sensor networks with quantized measurements, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 49, no. 4, pp. 2353–2368, 2013.

[52] R. Caballero-Águila, A. Hermoso-Carazo and J. Linares-Pérez, Networked fusion estimation with multiple uncertainties and time-correlated channel noise, *Information Fusion*, vol. 54, pp. 161–171, 2020.

[53] M. S. Arulampalam, S. Maskell, N. Gordon and T. Clapp, A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking, *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, 2002.

[54] W. Song, Z. Wang, Z. Li, H. Dong and Q.-L. Han, Protocol-based particle filtering for nonlinear complex networks: Handling non-Gaussian noises and measurement censoring, *IEEE Transactions on Network Science and Engineering*, vol. 10, no. 1, pp. 128–139, 2023.

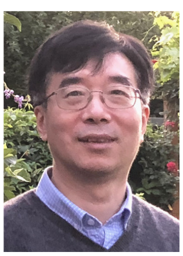
Citation information: DOI: 10.1109/TCYB.2025.3623631, IEEE Transactions on Cybernetics

[55] Y. Guo, Z. Wang, J.-Y. Li and Y. Xu, An impulsive approach to state estimation for multirate singularly perturbed complex networks under bit rate constraints, *IEEE Transactions on Cybernetics*, vol. 55, no. 3, pp. 1197–1209, 2025.

[56] T.-J. Liu, Z. Wang, Y. Liu and R. Wang, Unscented-Kalman-filter-based remote state estimation for complex networks with quantized measurements and amplify-and-forward relays, *IEEE Transactions on Cybernetics*, vol. 54, no. 11, pp. 6819–6831, 2024.

Weihao Song (Member, IEEE) received the B.S. degree in flight vehicle design and engineering in 2016 and the Ph.D. degree in aeronautical and astronautical science and technology in 2021, both from Beijing Institute of Technology, Beijing, China.

From May 2019 to May 2020, he was a Visiting Scholar with the Department of Computer Science, Brunel University London, Uxbridge, U.K. Since 2021, he has been a Postdoctoral Researcher at Peking University. He is also currently an Honorary Research Fellow with the Department of Computer Science, Brunel University London. His research interests include Bayesian state estimation, distributed state estimation, nonlinear filtering, and networked control systems.



Zidong Wang (Fellow, IEEE) received the B.Sc. degree in mathematics in 1986 from Suzhou University, Suzhou, China, and the M.Sc. degree in applied mathematics in 1990 and the Ph.D. degree in electrical engineering in 1994, both from Nanjing University of Science and Technology, Nanjing, China.

He is currently Professor of Dynamical Systems and Computing in the Department of Computer Science, Brunel University London, U.K. From 1990 to 2002, he held teaching and research appointments in universities in China, Germany and the UK. Prof. Wang's research interests include dynamical systems, signal processing, bioinformatics, control theory and applications. He has published a number of papers in international journals. He is a holder of the Alexander von Humboldt Research Fellowship of Germany, the JSPS Research Fellowship of Japan, William Mong Visiting Research Fellowship of Hong Kong.

Prof. Wang serves (or has served) as the Editor-in-Chief for *International Journal of Systems Science*, the Editor-in-Chief for *Neurocomputing*, the Editor-in-Chief for *Systems Science & Control Engineering*, and an Associate Editor for 12 international journals including IEEE Transactions on Automatic Control, IEEE Transactions on Control Systems Technology, IEEE Transactions on Neural Networks, IEEE Transactions on Signal Processing, and IEEE Transactions on Systems, Man, and Cybernetics-Part C. He is a Member of the Academia Europaea, a Member of the European Academy of Sciences and Arts, an Academician of the International Academy for Systems and Cybernetic Sciences, a Fellow of the IEEE, a Fellow of the Royal Statistical Society and a member of program committee for many international conferences.

Zhongkui Li (Senior Member, IEEE) received the B.S. degree in space engineering from the National University of Defense Technology, Changsha, China, in 2005, and the Ph.D. degree in dynamical systems and control from Peking University, Beijing, China, in 2010.

Since 2013, he has been with Peking University, where he is currently a Full Professor with the School of Advanced Manufacturing and Robotics. His current research interests include cooperative control and planning of multi-agent systems.

Dr. Li was the recipient of the China National Science Funds for Distinguished Young Scientists in 2024, the State Natural Science Award of China in 2015, the Natural Science Award of the Ministry of Education of China in 2022 and 2011, and the National Excellent Doctoral Thesis Award of China in 2012. His coauthored papers received the IET Control Theory & Applications Premium Award in 2013 and the Best Paper Award of *Journal of Systems Science & Complexity* in 2012. He serves as an Associate Editor for *IEEE Transactions on Automatic Control*, and several other journals.

Hongli Dong (Senior Member, IEEE) received the Ph.D. degree in control science and engineering from the Harbin Institute of Technology, Harbin, China, in 2012.

From 2009 to 2010, she was a Research Assistant with the Department of Applied Mathematics, City University of Hong Kong, Hong Kong. From 2010 to 2011, she was a Research Assistant with the Department of Mechanical Engineering, The University of Hong Kong, Hong Kong. From 2011 to 2012, she was a Visiting Scholar with the Department of Information Systems and Computing, Brunel University London, Uxbridge, U.K. From 2012 to 2014, she was an Alexander von Humboldt Research Fellow with the University of Duisburg-Essen, Duisburg, Germany. She is currently a Professor with the Artificial Intelligence Energy Research Institute, Northeast Petroleum University, Daqing, China. She is also the Director of the Heilongjiang Provincial Key Laboratory of Networking and Intelligent Control, Daqing. Her current research interests include robust control and networked control systems.

Prof. Dong is a very active reviewer for many international journals.