Protocol-Based Particle Filtering for Nonlinear Complex Networks: Handling Non-Gaussian Noises and Measurement Censoring

Weihao Song, Zidong Wang, Zhongkui Li, Hongli Dong, and Qing-Long Han

***Abstract*—In this paper, the particle filtering problem is investigated for a class of discrete-time nonlinear complex networks with stochastic perturbations under the scheduling of random access protocol. The stochastic perturbations stem from the on-off stochastic coupling, non-Gaussian noises and measurement censoring. The random occurrence of the on-off node coupling is governed by a set of Bernoulli distributed white sequences, and two kinds of measurement censoring models (i.e. dead-band-like model and saturation-like model) are characterized by the predetermined left- and right-end censoring thresholds. To alleviate data collision over the networks, the so-called random access protocol is elaborately exploited to orchestrate the process of measurement transmission. Moreover, two expressions of the modified likelihood function are established to weaken the adverse effects from the measurement censoring. Accordingly, a protocol-based filter is designed in the auxiliary particle filtering framework, where the new particles are generated from a mixture distribution and the associated weights are assigned based on the derived likelihood function. Finally, a multi-target tracking application is taken into account to demonstrate the practicability and effectiveness of the developed filtering scheme.**

***Index Terms*—Nonlinear/non-Gaussian complex network, particle filtering, random access protocol, on-off stochastic coupling, measurement censoring**

I. Introduction

Owing to its distinctive capability of characterizing different kinds of real-world systems, the complex network (CN) has recently aroused a surge of research interests from several branches of science and engineering such as sociology, economics, computer science, and electrical engineering [5], [12], [43]. Generally speaking, a typical CN is composed of a bulk of coupled and interacted nodes, and each node possesses its own practical characteristics and dynamical behaviors. To ascertain the collective behaviors of dynamical CNs, a great deal of attention has been devoted to the analysis and synthesis issues on various CNs in recent years, and a large number of results have sprung up from a variety of perspectives such as structure identification [56], stability analysis [52], synchronization [7], and so forth. In particular, despite its great significance in practical applications, the complete information about network states is *unlikely* to be fully accessible because of the complicated structures and constrained resources, and therefore the filtering (or state estimation) problem has gradually become an active research topic in the realm of CNs.

In the context of filtering or state estimation over CNs, most of the existing results have been concerned with network structures/topologies, security issues and network-induced phenomena, see e.g. [8], [35] on switching topology, [20], [46] on deception attacks, [39] on gain variations, and [55] on packet dropouts. It is worth mentioning that the filter design is largely dependent on the system model and noise types. So far, the majority of published literature has been concentrated on linear systems or systems undergoing some specific nonlinearities such as sector-bounded nonlinearity [41], randomly occurring nonlinearity [33] and differentiable nonlinearity [21], [34], [36]. Also, the system noises have been typically assumed to be of Gaussian type [35] or norm-bounded [18], and such assumptions might be unrealistic in many real-world applications. As such, it makes practical sense to investigate the filtering issues for CNs with general nonlinearities and non-Gaussian noises, which remain open yet challenging, especially when the on-off stochastic coupling [27], [34] is taken into consideration as well.

With the ever-growing popularity of networked control systems, more and more system components (e.g., sensors, actuators and controllers) have now had their communications over shared communication networks [23], [42], [57]. Clearly, the inherently limited bandwidth of communication networks would lead to traffic congestions and, furthermore, certain network-induced phenomena (see [4], [6], [9], [28], [32], [49] and the references therein). Such kind of phenomena, if not properly refrained, would result in severe deterioration of system performance. In this regard, the so-called communication scheduling protocols have been exploited with aim to schedule the transmission process of massive data, and some representative protocols include event-triggered protocol [24],

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[38], Round-Robin protocol [15], [22], weighted try-once-discard protocol [47] and random access protocol [14], [48], [60]. Among others, the random access protocol has stood out as an extensively utilized one that attracts an ongoing research interest in the past decade [19], [50]. For example, the protocol-based resilient state estimation issue has been considered in [54] for a kind of time-delayed CNs with sector-bounded nonlinearities.

It should be pointed out that, in the most existing literature, an underlying assumption is that the sensor is able to produce ideal measurements at all times. Unfortunately, such an assumption might be restrictive in engineering practice because of intrinsic physical limitations (e.g. sensor resolution and range) and complicated external environments, and this is especially true for low-cost commercial sensors. To be more specific, the sensor outputs are continuous functions of system states within a prescribed dynamic range but are constant outside such a range, and this phenomenon is customarily referred to as the measurement censoring [2], [31], [59].

In the context of measurement censoring, there have been mainly two kinds of censoring models reported in the literature, namely, the dead-band-like censoring [30], [51] and the saturation-like censoring [1]. In order to attenuate the effect from censored measurements on system performance, some elegant results have been obtained on the filtering issues subject to measurement censoring, see [16], [25] and the references therein. For example, the multi-sensor fusion problem has been addressed in [51] for a class of linear systems with dead-band-like measurements and event-triggered mechanism. Nevertheless, when it comes to general nonlinear CNs, the relevant results have been very few on the censoring-measurement-based filtering problem despite its conspicuous engineering significance.

Motivated by the above discussions, the main purpose of this paper is to deal with the protocol-based particle filtering problem for a general class of nonlinear CNs with simultaneous consideration of non-Gaussian noises, on-off stochastic coupling and measurement censoring. In doing so, three foreseeable challenges emerge as follows: 1) how to establish a suitable model that concurrently characterizes the non-Gaussian noise, measurement censoring and the scheduling of random access protocol? 2) how to propagate the new particles in the presence of on-off stochastic coupling? and 3) how to mitigate the impacts from censored and scheduled measurements on the filtering performance by updating the importance weights? It is, therefore, our interest in overcoming the above identified challenges by developing an appropriate particle filtering algorithm.

The main contributions of this paper can be highlighted as follows: *1) the addressed filtering problem is fairly comprehensive that not only focuses on a general class of nonlinear CN but also covers the on-off stochastic coupling, non-Gaussian noises, measurement censoring and random access protocol; 2) two explicit expressions of likelihood function are constructed by taking into account the effect of random access protocol and dead-band-like/saturation-like measurement censoring; and 3) an easy-to-implement protocol-based auxiliary particle filtering algorithm is developed by resorting to the modified particle propagation and the compensated weight update.*

The remainder of this paper is arranged as follows. Section II formulates the problem under investigation and provides some preliminaries about the auxiliary particle filtering scheme. The protocol-based particle filtering algorithm is proposed and discussed in Section III. In Section IV, a multi-target tracking application is considered and the simulation results are presented to illustrate the effectiveness of the developed particle filter. Some concluding remarks are given in Section V.

Notation. Throughout this paper, the notation used is fairly standard. $\mathbb{R}^n$ represents the n-dimensional Euclidean vector space. $p_x(\cdot)$ characterizes the probability density function of a stochastic variable x, namely, $x \sim p_x(\cdot)$, and $p(x|y)$ stands for the probability density function of x conditional on y. $\Pr\{A\}$ denotes the occurrence probability of the discrete event A. $\|\cdot\|$ represents the Euclidean norm. The superscript T denotes the matrix operation of transpose. $x_{i:j}$ denotes the trajectory of x from time instant i to time instant j. Other notations will be given if necessary.

II. Problem Formulation and Preliminaries

A. Problem formulation

Consider the following discrete-time CN consisting of N coupled nodes

$$x_{k+1}^i = f_k^i(x_k^i) + \alpha_k^i \sum_{j=1}^{N} c^{ij} g_k^{ij}(x_k^j) + \omega_k^i \tag{1}$$

where, for $i = 1, 2, \ldots, N$, $x_k^i \in \mathbb{R}^n$ is the local state of the ith node at time instant k; $f_k^i(\cdot) : \mathbb{R}^n \mapsto \mathbb{R}^n$ and $g_k^{ij}(\cdot) : \mathbb{R}^n \mapsto \mathbb{R}^n$ are both known nonlinear functions; $\omega_k^i \in \mathbb{R}^n$ represents the process noise satisfying $p_{\omega_k^i}(\cdot)$; $c^{ij} \geq 0$ denotes the coupling strength between node i and node j; and α_k^i is introduced to characterize the on-off random coupling property of the considered CN, which is modeled as a Bernoulli distributed random variable with the following probability distribution

$$\begin{cases} \Pr\{\alpha_k^i = 1\} = \bar{\alpha}^i \\ \Pr\{\alpha_k^i = 0\} = 1 - \bar{\alpha}^i \end{cases} \tag{2}$$

where $\bar{\alpha}^i \in [0, 1]$ stands for the random coupling rate.

For each node i, the measurements are taken by S sensors, and the measurement output of the sth sensor is established as

$$\bar{y}_k^{i,s} = h_k^{i,s}(x_k^i) + \nu_k^{i,s} \tag{3}$$

where, for $s = 1, 2, \ldots, S$, $\bar{y}_k^{i,s} \in \mathbb{R}$ denotes the measurement output of the sth sensor for node i at time instant k, $h_k^{i,s}(\cdot) : \mathbb{R}^n \mapsto \mathbb{R}$ represents the known nonlinear measurement function, and $\nu_k^{i,s} \in \mathbb{R}$ denotes the measurement noise on the sth sensor, which has the probability density function $p_{\nu_k^{i,s}}(\cdot)$.

To better formulate the problem to be investigated, we make three common assumptions as follows.

Assumption 1: The prior knowledge of the initial state x_0^i is included in the known probability density function $p_{x_0^i}(\cdot)$.

Assumption 2: The process noise ω_k^i, the measurement noise $\nu_k^{i,s}$ and the random variable α_k^i are mutually independent, and they are also independent of the initial state x_0^i.

Assumption 3: The probability density functions $p_{\omega_k^i}(\cdot)$ and $p_{\nu_k^{i,s}}(\cdot)$ of the process noise and measurement noise are known.

Due to physical/hardware limitations of deployed sensors and the complicated working environment, the sensors might be prone to the phenomenon of measurement censoring. In this paper, to cater for the practical engineering in a comprehensive way, we consider the following two kinds of censoring model [1], [51]:

$$\hat{y}_k^{i,s} = \begin{cases} \bar{y}_k^{i,s}, & \bar{y}_k^{i,s} \geq y_r^{i,s}, \\ y_{\text{const}}^{i,s}, & y_l^{i,s} < \bar{y}_k^{i,s} < y_r^{i,s}, \\ \bar{y}_k^{i,s}, & \bar{y}_k^{i,s} \leq y_l^{i,s}, \end{cases} \tag{4}$$

and

$$\hat{y}_k^{i,s} = \begin{cases} y_r^{i,s}, & \bar{y}_k^{i,s} \geq y_r^{i,s}, \\ \bar{y}_k^{i,s}, & y_l^{i,s} < \bar{y}_k^{i,s} < y_r^{i,s}, \\ y_l^{i,s}, & \bar{y}_k^{i,s} \leq y_l^{i,s}, \end{cases} \tag{5}$$

where $y_r^{i,s}$ and $y_l^{i,s}$ denote, respectively, the right- and left-end censoring thresholds of the sth sensor for node i, and $y_{\text{const}}^{i,s}$ stands for the constant output (usually given by $(y_r^{i,s}+y_l^{i,s})/2$) when the sensor is trapped in the dead zone. A schematic diagram comparing the considered censoring models (4) (purple solid line) and (5) (blue dotted line) is illustrated in Fig. 1.

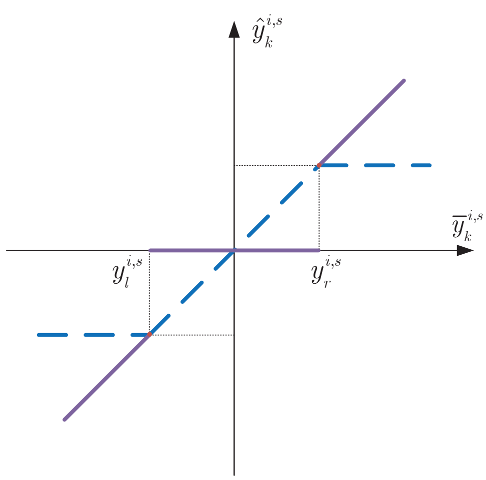

Fig. 1: A schematic diagram for the considered two censoring models.

Remark 1: As a matter of fact, the model (4), which is usually referred to as the dead-band-like censoring model in the literature, describes common engineering practice. For example, it is often the case in practical implementations that a ring laser gyro sensor suffers from the dead-band-like censoring due primarily to the inherent lock-in characteristic and mechanical stiction [17]. A similar phenomenon called voltage dead band also exists in the application of power transmitters [40]. On the other hand, the model (5), named as the saturation-like censoring model, stems mainly from the physical constraints of the sensors themselves with examples including insufficient range of sensor instrumentation and the saturation of amplifier in circuits [53]. In real-world implementations, the right- and left-end censoring thresholds can be obtained from the manufacturers in advance or determined by experimental measurements.

It is clear that simultaneous transmission of massive sensor measurements would inevitably lead to the phenomenon of data collision. For the purpose of alleviating such a phenomenon and reducing the network resource consumption, the so-called random access protocol is employed in this paper to schedule the order of the measurement transmission. Without loss of generality, let us evenly classify the sensors for node i into M sensor groups (i.e., $S = bM$, where b is a positive integer) according to the spatial distribution or specific task allocation. Then, only one sensor group can be granted the access opportunity to the corresponding communication network at each time instant. For each node i, let $\rho_k^i \in \{1, 2, \ldots, M\}$ be the chosen sensor group that has the access to transmit the current measurements to the remote filter at time instant k.

To characterize the random nature of the scheduling protocol, $\{\rho_k^i\}_{k\geq 0}$ is modeled as an independent and identically distributed stochastic process with probability distribution given as follows:

$$\Pr\{\rho_k^i = m\} = p_m^i, \quad m = 1, 2, \ldots, M \tag{6}$$

where p_m^i ($0 \leq p_m^i \leq 1$), which satisfies $\sum_{m=1}^{M} p_m^i = 1$, denotes the occurrence probability for the mth sensor group to gain the privilege to communicate with the remote filter corresponding to node i.

Denote by

$$\tilde{y}_k^{i,m} = [\hat{y}_k^{i,m_1}, \hat{y}_k^{i,m_2}, \ldots, \hat{y}_k^{i,m_b}]^T$$

the measurements collected by the mth sensor group for node i. Then, under the random access protocol, the available measurements for the remote filter associated with node i can be described by

$$y_k^i = \sum_{m=1}^{M} \delta(\rho_k^i - m)\tilde{y}_k^{i,m} \tag{7}$$

where $\delta(\cdot)$ represents the Kronecker delta function, which equals one if $\rho_k^i = m$ and equals zero otherwise.

B. Preliminary knowledge

For the sequential Bayesian filtering problem, the core task is to derive the posterior probability density function of state of interest. For example, consider the target plant and sensors with the following dynamics:

$$\begin{cases} x_{k+1} = f_k(x_k, u_k, \omega_k) \\ y_k = h_k(x_k, \nu_k) \end{cases} \tag{8}$$

where u_k is the known input vector, and the definitions of other variables are similar to those in Section II-A except for the superscripts. Then, the posterior probability density function $p(x_{k+1}|y_{1:k+1},u_{0:k+1})$ can be obtained in the following recursive form [26]:

$$\begin{cases} p(x_{k+1}|y_{1:k},u_{0:k}) \\ \qquad = \int p(x_{k+1}|x_k,u_k)p(x_k|y_{1:k},u_{0:k})dx_k, \\ p(x_{k+1}|y_{1:k+1},u_{0:k+1}) \\ \qquad = \dfrac{p(y_{k+1}|x_{k+1})p(x_{k+1}|y_{1:k},u_{0:k})}{\int p(y_{k+1}|x_{k+1})p(x_{k+1}|y_{1:k},u_{0:k})dx_{k+1}}. \end{cases} \tag{9}$$

For clarity, in the subsequent analysis of this paper, we denote $p(x_{k+1}|y_{1:k+1},u_{0:k+1})$ as $p(x_{k+1}|y_{1:k+1},u_{0:k})$ by considering that the state at time instant $k+1$ (i.e., x_{k+1}) is independent of u_{k+1}.

Note that the multidimensional integrals involved in (9) render it difficult to derive the analytical expression of $p(x_{k+1}|y_{1:k+1},u_{0:k})$ in most cases. As an alternative, we resort to the Monte Carlo numerical approximation and the importance sampling technique. Then, the minimum mean-square error estimate can be acquired as [3]

$$\hat{x}_{k+1} = \int x_{k+1}p(x_{k+1}|y_{1:k+1},u_{0:k})dx_{k+1} \approx \sum_{d=1}^{D} w_{k+1}^{\{d\}}x_{k+1}^{\{d\}} \tag{10}$$

where D denotes the total number of sampled particles and $x_{k+1}^{\{d\}}$ represents the dth particle sampled from a proposal distribution with associated weight $w_{k+1}^{\{d\}}$.

In most practical implementations, the state transition density $p(x_{k+1}|x_k^{\{d\}},u_k)$ is chosen as the proposal distribution due to its easy operation and simplicity. Nevertheless, the neglection of current measurement information during the particle update might decrease the efficiency of importance sampling and give rise to unbearable performance decrements. To this end, the auxiliary particle filtering scheme [45] emerges as an effective way of getting round the problem, which aims to improve the compatibility between new measurements and updated particles. In this case, a set of intermediate particles $\{\eta_{k+1}^{\{d\}}\}_{d=1,2,\ldots,D}$ is first drawn from $p(x_{k+1}|x_k^{\{d\}},u_k)$, and the corresponding indices ϵ_d are generated based on the probabilities proportional to $w_k^{\{d\}}p(y_{k+1}|\eta_{k+1}^{\{d\}})$. Then, the new particles can be updated as

$$x_{k+1}^{\{d\}} \sim p(x_{k+1}|x_k^{\{\epsilon_d\}},u_k),$$

and the update rule of the associated weights is

$$w_{k+1}^{\{d\}} = \frac{p(y_{k+1}|x_{k+1}^{\{d\}})}{p(y_{k+1}|\eta_{k+1}^{\{\epsilon_d\}})}. \tag{11}$$

The aim of this paper is to propose a protocol-based auxiliary particle filtering algorithm for a kind of nonlinear/non-Gaussian CNs with on-off stochastic coupling such that the minimum mean-square error estimation can be ensured based on the censored and scheduled measurements.

III. Design of The Particle Filter

In this section, we set about designing the auxiliary particle filtering algorithm based on the censored measurements and the scheduling of random access protocol. As with the standard particle filtering framework, the foremost procedures in the filter design include the two stages of particle propagation and importance weight update, which will be discussed in detail in the subsequent analysis.

Recalling the dynamics of target plant described in (1), it is clear that the state propagation of the node i is dependent on the state of node j due to the complex coupling characteristics between nodes, which renders additional difficulties to the design of particle filter. To deal with such an issue, similar to the description of (8), the states x_k^j are collectively regarded as the input u_k^i of the dynamics of node i at the current stage. However, it is still difficult to directly draw samples from $p(x_{k+1}^i|x_k^{i,\{d\}},u_k^i)$ due to the fact that the input u_k^i (actually the states x_k^j of other nodes) is unknown and the CN is subject to the on-off coupling. To this end, we utilize the estimates $\hat{x}_k^j$ (which are available at time instant k) to approximate the unknown u_k^i. Furthermore, based on the law of total probability as well as the probability distribution given in (2), one has

$$\begin{aligned} & p(x_{k+1}^i|x_k^{i,\{d\}},u_k^i) \\ =\ & p(x_{k+1}^i,\alpha_k^i=1|x_k^{i,\{d\}},u_k^i) \\ & + p(x_{k+1}^i,\alpha_k^i=0|x_k^{i,\{d\}},u_k^i) \\ =\ & \Pr\{\alpha_k^i=1\}p(x_{k+1}^i|\alpha_k^i=1,x_k^{i,\{d\}},u_k^i) \\ & + \Pr\{\alpha_k^i=0\}p(x_{k+1}^i|\alpha_k^i=0,x_k^{i,\{d\}},u_k^i) \\ =\ & \bar{\alpha}^i p(x_{k+1}^i|\alpha_k^i=1,x_k^{i,\{d\}},u_k^i) \\ & + (1-\bar{\alpha}^i)p(x_{k+1}^i|\alpha_k^i=0,x_k^{i,\{d\}},u_k^i) \\ \approx\ & \bar{\alpha}^i p(x_{k+1}^i|\alpha_k^i=1,x_k^{i,\{d\}},\hat{x}_k^j) \\ & + (1-\bar{\alpha}^i)p(x_{k+1}^i|\alpha_k^i=0,x_k^{i,\{d\}}). \end{aligned} \tag{12}$$

Remark 2: It should be emphasized that, due to the complex on-off coupling characteristics between nodes, the new particle $x_{k+1}^{i,\{d\}}$ (or the intermediate one $\eta_{k+1}^{i,\{d\}}$) is drawn from a mixture distribution characterized by (12) and the state estimates $\hat{x}_k^j$ of other nodes are utilized. Meanwhile, the mixing probability is dependent on the random coupling rate.

In what follows, for each node i, we aim to derive an update rule for the importance weights $w_{k+1}^{i,\{d\}}$ by establishing an explicit expression of the likelihood function $p(y_{k+1}^i|x_{k+1}^{i,\{d\}})$ under the consideration of censored and scheduled measurements.

To facilitate the subsequent analysis, let us define an indicator function as

$$1_\Xi(x) = \begin{cases} 1, & \text{if } x \in \Xi, \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

Proposition 1: For each node i, consider the measurement model (3), dead-band-like censoring model (4) as well as the random access protocol described by (6) and (7). At time instant $k+1$, the full likelihood function associated with node i and the dth particle can be expressed as

$$p(y_{k+1}^i|x_{k+1}^{i,\{d\}}) = \sum_{m=1}^{M} p_m^i \prod_{j=1}^{b} p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}}) \tag{14}$$

where

$$
\begin{aligned}
&p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}})\\
&=1_{\Xi_1^{i,m_j}}(y_{k+1}^{i,j})p_{\nu_{k+1}^{i,m_j}}(y_{k+1}^{i,j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\\
&\quad+1_{\{y_{\text{const}}^{i,m_j}\}}(y_{k+1}^{i,j})\big[cdf_{\nu_{k+1}^{i,m_j}}(y_r^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\\
&\quad-cdf_{\nu_{k+1}^{i,m_j}}(y_l^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\big],\\
&\Xi_1^{i,m_j}=(-\infty,y_l^{i,m_j}]\cup[y_r^{i,m_j},\infty),
\end{aligned}
$$

and $cdf_{\nu_{k+1}^{i,m_j}}(\cdot)$ denotes the cumulative distribution function of the stochastic noise ν_{k+1}^{i,m_j}.

Proof: According to the law of total probability, it is clear that

$$
\begin{aligned}
&p(y_{k+1}^{i}|x_{k+1}^{i,\{d\}})\\
&=\sum_{m=1}^{M}p(y_{k+1}^{i},\rho_{k+1}^{i}=m|x_{k+1}^{i,\{d\}})\\
&=\sum_{m=1}^{M}p(y_{k+1}^{i}|\rho_{k+1}^{i}=m,x_{k+1}^{i,\{d\}})\Pr\{\rho_{k+1}^{i}=m|x_{k+1}^{i,\{d\}}\}.
\end{aligned}
\tag{15}
$$

Then, substituting (6) and (7) into (15) yields

$$
\begin{aligned}
&p(y_{k+1}^{i}|x_{k+1}^{i,\{d\}})\\
&=\sum_{m=1}^{M}p_m^ip(\sum_{j=1}^{M}\delta(\rho_{k+1}^{i}-j)\tilde{y}_{k+1}^{i,j}|\rho_{k+1}^{i}=m,x_{k+1}^{i,\{d\}})\\
&=\sum_{m=1}^{M}p_m^ip(\tilde{y}_{k+1}^{i,m}|x_{k+1}^{i,\{d\}}).
\end{aligned}
\tag{16}
$$

On the other hand, it follows from Assumption 3 that

$$
p(\tilde{y}_{k+1}^{i,m}|x_{k+1}^{i,\{d\}})=\prod_{j=1}^{b}p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}}).\tag{17}
$$

Recall the censoring model (4) and note that $y_{k+1}^{i,j}=\hat{y}_{k+1}^{i,m_j}$ when $\rho_{k+1}^{i}=m$. It follows that, if $y_{k+1}^{i,j}\geq y_r^{i,m_j}$ or $y_{k+1}^{i,j}\leq y_l^{i,m_j}$, one has

$$
\begin{aligned}
p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}})&=p(\bar{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}})\\
&=p_{\nu_{k+1}^{i,m_j}}(y_{k+1}^{i,j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}})).
\end{aligned}
\tag{18}
$$

In addition, if $y_{k+1}^{i,j}=y_{\text{const}}^{i,m_j}$, we have

$$
\begin{aligned}
p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}})&=p(y_l^{i,m_j}<\bar{y}_{k+1}^{i,m_j}<y_r^{i,m_j}|x_{k+1}^{i,\{d\}})\\
&=cdf_{\nu_{k+1}^{i,m_j}}(y_r^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\\
&\quad-cdf_{\nu_{k+1}^{i,m_j}}(y_l^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}})).
\end{aligned}
\tag{19}
$$

Similar to the expression in [2], we can rewrite (18) and (19) as follows:

$$
\begin{aligned}
&p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}})\\
&=1_{(-\infty,y_l^{i,m_j}]\cup[y_r^{i,m_j},\infty)}(y_{k+1}^{i,j})p_{\nu_{k+1}^{i,m_j}}(y_{k+1}^{i,j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\\
&\quad+1_{\{y_{\text{const}}^{i,m_j}\}}(y_{k+1}^{i,j})\big[cdf_{\nu_{k+1}^{i,m_j}}(y_r^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\\
&\quad-cdf_{\nu_{k+1}^{i,m_j}}(y_l^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\big].
\end{aligned}
\tag{20}
$$

Together with (16), (17) and (20), we can readily arrive at (14), which completes the proof. ■

Next, we are going to present the results with respect to the saturation-like censoring model and the random access protocol.

Proposition 2: For each node i, consider the measurement model (3), saturation-like censoring model (5) as well as the random access protocol described by (6) and (7). At time instant $k+1$, the full likelihood function associated with node i and the dth particle can be expressed as

$$
p(y_{k+1}^{i}|x_{k+1}^{i,\{d\}})=\sum_{m=1}^{M}p_m^i\prod_{j=1}^{b}p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}})\tag{21}
$$

where

$$
\begin{aligned}
&p(\hat{y}_{k+1}^{i,m_j}|x_{k+1}^{i,\{d\}})\\
&=1_{\Xi_2^{i,m_j}}(y_{k+1}^{i,j})p_{\nu_{k+1}^{i,m_j}}(y_{k+1}^{i,j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\\
&\quad+1_{\{y_r^{i,m_j}\}}(y_{k+1}^{i,j})\big[1-cdf_{\nu_{k+1}^{i,m_j}}(y_r^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\big]\\
&\quad+1_{\{y_l^{i,m_j}\}}(y_{k+1}^{i,j})cdf_{\nu_{k+1}^{i,m_j}}(y_l^{i,m_j}-h_{k+1}^{i,m_j}(x_{k+1}^{i,\{d\}}))\big],
\end{aligned}
$$

and $\Xi_2^{i,m_j}=(y_l^{i,m_j},y_r^{i,m_j})$.

Proof: The proof can be carried out by following the similar line of Proposition 1, and is therefore omitted here for conciseness. ■

Now, based on the established expressions of the full likelihood function in Propositions 1 and 2, the importance weight in regard to node i and the dth particle can be updated as

$$
w_{k+1}^{i,\{d\}}=\frac{p(y_{k+1}^{i}|x_{k+1}^{i,\{d\}})}{p(y_{k+1}^{i}|\eta_{k+1}^{i,\{\epsilon_{i,d}\}})}\tag{22}
$$

where $\eta_{k+1}^{i,\{\epsilon_{i,d}\}}$ denotes the corresponding intermediate particle before particle update.

For ease of illustration, the overall structure of the proposed protocol-based particle filtering algorithm is summarized in Algorithm 1.

Remark 3: It is worth noting that, compared with the existing results concerning the state estimation problem of nonlinear CN (e.g. [34], [36]), the main advantages of the proposed filtering algorithm lie in that it does not impose strict requirement (e.g. differentiability and continuity) on the type of nonlinear function and, more importantly, is not restricted to the case of Gaussian noises. On the other hand, when the random coupling rate becomes $\bar{\alpha}=0$, the considered target plant (1) will degrade to the standard nonlinear system (without node coupling behaviors), and the mixture distribution (12)

Algorithm 1 Protocol-based auxiliary particle filtering algorithm for CN with nonlinear coupling and measurement censoring (executed on target node i)

Initialization: For target node i, draw D particles with equal weights from the prior density, i.e., $x_0^{i,\{d\}} \sim p_{x_0^i}(\cdot)$, $d = 1, 2, \ldots, D$, and set the maximum recursive step as K.

for $k = 0, 2, \ldots, K-1$ **do**

  Step 1: Measurement collection

  Under the scheduling of random access protocol (6) and (7), receive the censored measurements y_{k+1}^i with the censoring model (4) or (5).

  Step 2: Intermediate particle generation

  Sample intermediate particles $\{\eta_{k+1}^{i,\{d\}}\}_{d=1,2,\ldots,D}$ from $p(x_{k+1}^i|x_k^{i,\{d\}}, u_k^i)$ according to (12), and generate the particle indices $\{\epsilon_{i,d}\}_{d=1,2,\ldots,D}$ based on probabilities proportional to $w_k^{i,\{d\}} p(y_{k+1}^i|\eta_{k+1}^{i,\{d\}})$, where the term $p(y_{k+1}^i|\eta_{k+1}^{i,\{d\}})$ is calculated by (14) or (21).

  Step 3: Particle propagation

  Based on indices $\{\epsilon_{i,d}\}_{d=1,2,\ldots,D}$ and (12), draw the particles $\{x_{k+1}^{i,\{d\}}\}_{d=1,2,\ldots,D}$ as

$$x_{k+1}^{i,\{d\}} \sim p(x_{k+1}^i|x_k^{i,\{\epsilon_{i,d}\}}, u_k^i).$$

  Step 4: Weight update

  Update the unnormalized importance weight $\bar{w}_{k+1}^{i,\{d\}}$ according to (22).

  Step 5: Weight normalization

  Normalize the weights according to

$$w_{k+1}^{i,\{d\}} = \frac{\bar{w}_{k+1}^{i,\{d\}}}{\sum_{j=1}^{D} \bar{w}_{k+1}^{i,\{j\}}}.$$

  Step 6: State estimation

  Update the state estimate as

$$\hat{x}_{k+1}^i = \sum_{d=1}^{D} w_{k+1}^{i,\{d\}} x_{k+1}^{i,\{d\}}$$

end for

will boil down to the common prior density $p(x_{k+1}^i|x_k^{i,\{d\}})$. In addition, it can be seen from the dead-band-like censoring model (4) as well as the likelihood function (14) that, if the right- and left-end censoring thresholds $y_r^{i,s}$ and $y_l^{i,s}$ are equal, then the modified particle filtering algorithm developed in this paper will reduce to the case where only the random access protocol is considered. Similar results can also be obtained for the case of saturation-like censoring (5) and (21) if we set $y_r^{i,s} = +\infty$ and $y_l^{i,s} = -\infty$. As such, the system under consideration is fairly general and the proposed particle filtering algorithm exhibits great application potentials.

Remark 4: It should be pointed out that for the standard particle filter, there have been some theoretical analysis results available in the literature [10], [11]. In fact, the particle approximation will approach the true probability density function, as the number of particles tends to infinity [3]. More importantly, it has been revealed in [11] that the convergence of the mean square error toward zero can be guaranteed with the convergence rate proportional to $1/D$ provided that the importance weights are upper bounded and the standard resampling scheme is utilized. Based on these facts, the convergency analysis of a modified particle filter has been briefly conducted in [58] by assuming that the involved probability densities (e.g. the established likelihood function) are bounded. In addition, the auxiliary particle filter has been reinterpreted as a standard particle filter in [29] and the corresponding convergence results have been adapted from those of the standard one. As such, the simple convergence of the proposed algorithm can be analyzed by following the similar line. Nevertheless, it is really a tough task to conduct a rigorous analysis on the convergence of the proposed algorithm with mild assumptions due to the involved system complexities, which deserves further investigation in our future research.

Remark 5: Up to now, the protocol-based filtering problem has been addressed for a class of nonlinearly coupled CN in the simultaneous presence of on-off coupling behaviors, non-Gaussian noises and measurement censoring. To be more specific, the random coupling rate has been employed in the procedure of selecting and propagating particles through a mixture distribution. The effects of the two-side measurement censoring models (i.e., dead-band-like model and saturation-like model) and the random access protocol have been fully taken into consideration during the establishment of the likelihood functions. The addressed filtering problem in this paper is new and comprehensive, which can well reflect the engineering reality. Meanwhile, the proposed filtering algorithm with newly established sampling distribution and likelihood functions allows to attenuate the impacts of the complex factors involved in this paper.

IV. Simulation Experiments

In this section, a practical application regarding the tracking of multiple interacting targets is provided to illustrate the effectiveness and practical applicability of the proposed particle filtering algorithm.

Consider a scenario where three targets are tracked in a two-dimensional plane and the motions of each target are mutually interacted in an on-off fashion due primarily to the behaviors of collision avoidance or other specified mission requirements.

Denote by $[p_{x,k+1}^i, p_{y,k+1}^i, \phi_{k+1}^i]^T$ the state vector of target node i ($i = 1, 2, 3$) at time instant $k+1$, where $(p_{x,k+1}^i, p_{y,k+1}^i)$ denotes the target position and ϕ_{k+1}^i stands for the target orientation. Then, the motion model of target node i, adopted from [34], [37], can be described as

$$\begin{aligned} \begin{bmatrix} p_{x,k+1}^i \\ p_{y,k+1}^i \\ \phi_{k+1}^i \end{bmatrix} &= \begin{bmatrix} p_{x,k}^i \\ p_{y,k}^i \\ \phi_k^i \end{bmatrix} + \begin{bmatrix} v_k^i \cos\phi_k^i \\ v_k^i \sin\phi_k^i \\ \Omega_k^i \end{bmatrix} \\ &\quad + \alpha_k^i \sum_{j=1}^{3} c^{ij} \begin{bmatrix} \sin p_{x,k}^j \\ \sin p_{y,k}^j \\ \sin \phi_k^j \end{bmatrix} + \omega_k^i \end{aligned} \tag{23}$$

where v_k^i and Ω_k^i denote, respectively, the velocity and angular velocity of target node i.

In order to track the considered three targets, the passive received-signal strength sensors are deployed/distributed in the surveillance region of interest. For each target node i, S sensors are utilized and the measurement model of the sth received-signal strength sensor can be established as [13], [44]

$$\begin{aligned}\bar{y}^{i,s}_{k+1} = \Phi_0 - 10\eta\log_{10}\big((\|[p^i_{x,k+1}, p^i_{y,k+1}]^T \\ - [x^{i,s}, y^{i,s}]^T\|)/r_0\big) + \nu^{i,s}_{k+1}\end{aligned} \tag{24}$$

where Φ_0 stands for the received strength at the reference distance r_0, η denotes the path loss exponent, $(x^{i,s}, y^{i,s})$ represents the position of the sth sensor for node i, and $\nu^{i,s}_{k+1}$ denotes the measurement noise, which is a two-component Gaussian mixture with the following probability density function

$$\begin{aligned}p(\nu^{i,s}_{k+1}) = (1-\kappa^{i,s})\mathcal{N}(\nu^{i,s}_{k+1}; \mu^{i,s}_1, (\sigma^{i,s}_1)^2) \\ + \kappa^{i,s}\mathcal{N}(\nu^{i,s}_{k+1}; \mu^{i,s}_2, (\sigma^{i,s}_2)^2)\end{aligned} \tag{25}$$

where the notation $\mathcal{N}(\nu; \mu, \sigma^2)$ represents the Gaussian probability density function with mean μ and variance σ, and $\kappa^{i,s}$ denotes the glint probability associated with the sth sensor for node i.

Taking into account the scheduling of random access protocol, the S sensors for target node i are evenly divided into M groups, and at each time instant, only one group is granted the access to transmit the censored measurements (see (4) or (5)) to the remote particle filter.

To evaluate the tracking performance of the proposed filtering algorithm, a celebrated metric named root mean-square error (RMSE) is defined with respect to the position estimates over Q independent Monte Carlo runs, i.e.,

$$\mathrm{RMSE}_{i,k} = \sqrt{\frac{1}{Q}\sum_{q=1}^{Q}\Big[(p^{i,q}_{x,k} - \hat{p}^{i,q}_{x,k})^2 + (p^{i,q}_{y,k} - \hat{p}^{i,q}_{y,k})^2\Big]} \tag{26}$$

where $(p^{i,q}_{x,k}, p^{i,q}_{y,k})$ stands for a specific realization of the position of target node i at time instant k during the qth Monte Carlo run, and $(\hat{p}^{i,q}_{x,k}, \hat{p}^{i,q}_{y,k})$ denotes the corresponding estimate.

In the simulation, the number of sensors for each target node is set to be $S = 6$ and each sensor group is composed of three sensors (i.e., $M = 2$ and $b = 3$). The true initial states for three targets are, respectively, set as $x^1_0 = [16, 14, 0.2]^T$, $x^2_0 = [14, 20, 0.3]^T$ and $x^3_0 = [20, 26, 0.4]^T$. The process noises are Gaussian white noises with mean zero and covariance matrix $\mathrm{diag}\{[0.03^2, 0.03^2, 0.01^2]\}$. The initial 1000 particles are sampled from the Gaussian distribution with mean x^i_0 and covariance matrix $\mathrm{diag}\{[3^2, 3^2, 0.2^2]\}$. In addition, the random coupling rate is $\bar{\alpha}^i = 0.2$ for $i = 1, 2, 3$, and the coupling strength c^{ij} is selected to be 0.01 if $i \neq j$. For the received-signal strength sensors, the parameters are chosen as $\Phi_0 = 10$, $\eta = 2$, $r_0 = 1$, $\mu^{i,s}_1 = \mu^{i,s}_2 = 0$, $\sigma^{i,s}_1 = 1$, $\sigma^{i,s}_2 = 6$ and $\kappa^{i,s} = 0.2$. The thresholds in the dead-band-like censoring model (4) are selected as $y^{i,s}_r = 10$ and $y^{i,s}_l = -10$. Moreover, we have $p^i_1 = 0.2$ and $p^i_2 = 0.8$ for $i = 1, 2, 3$.

For one Monte Carlo run, based on Proposition 1 and Algorithm 1, the simulation results with respect to the dead-band-like censoring model (4) are depicted in Figs. 2-5. It can be observed from Figs. 2-4 that the proposed particle filtering scheme is capable of tracking the trajectories of the interacted three targets with satisfactory performance. Fig. 5 displays the behaviors of the scheduling protocol as well as the censored and scheduled measurement information for the first measurement component related to target node 1.

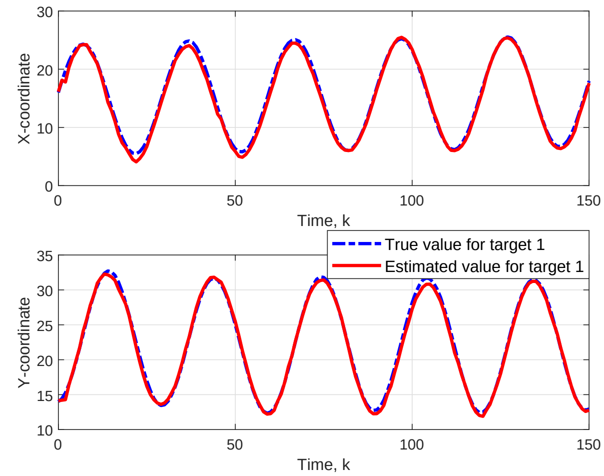

Fig. 2: True and estimated trajectories of target node 1.

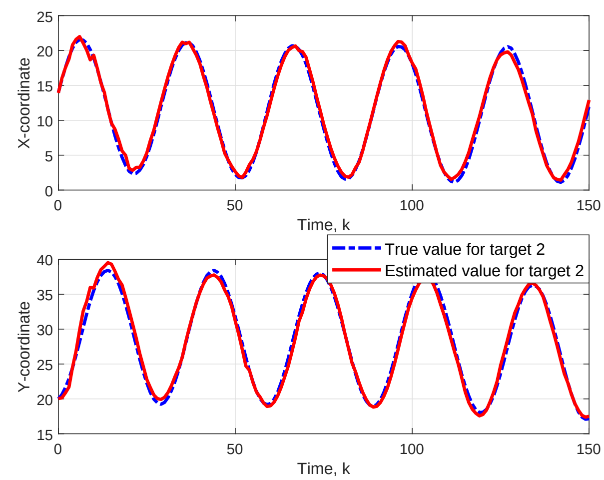

Fig. 3: True and estimated trajectories of target node 2.

In what follows, we are going to further show the effectiveness and performance superiority of the proposed filtering algorithm in the case of dead-band-like measurement censoring. To this end, the newly modified auxiliary particle filter (abbreviated as MAPF-DBLMC) is compared with other three filtering algorithms, namely, the modified auxiliary particle filter without considering the coupled target dynamics during particle generation (abbreviated as MAPF-DBLMC-NC), the auxiliary particle filter without considering the compensation of measurement censoring (abbreviated as MAPF-DBLMC-NMC), and the similarly modified particle filter in the standard sequential importance resampling framework (abbreviated as MPF-DBLMC). The corresponding simulation results, in terms of position RMSE over 300 independent Monte Carlo

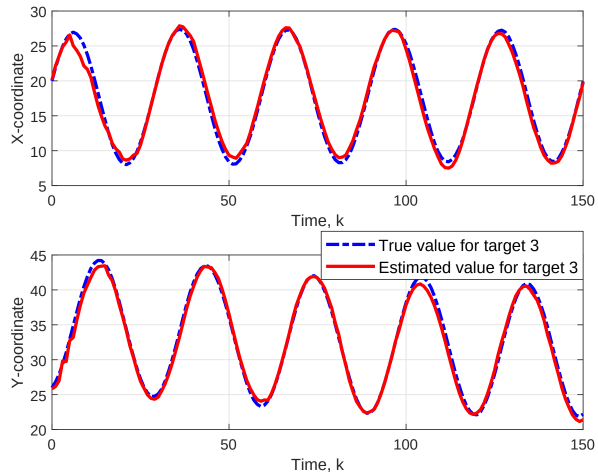

Fig. 4: True and estimated trajectories of target node 3.

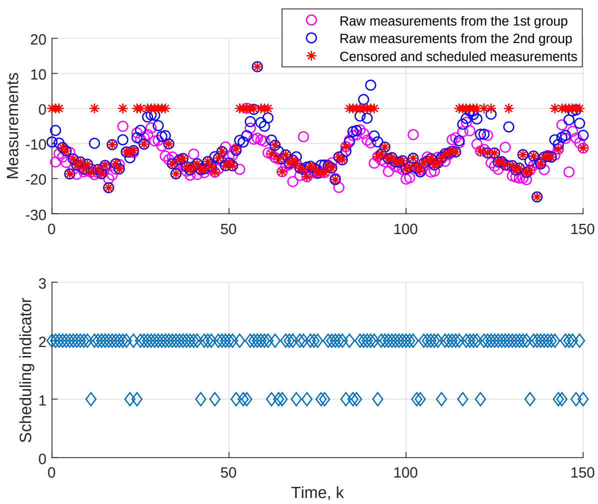

Fig. 5: The first measurement component associated with target node 1.

runs, are plotted in Figs. 6-8, and the average RMSEs are listed in TABLE I. As expected, the proposed filtering scheme performs satisfactorily due to the devoted effort during the design process of particle generation and weight update.

TABLE I: Average RMSEs of different algorithms with respect to dead-band-like censoring.

	Target 1	Target 2	Target 3	Average
MAPF-DBLMC	1.3662	1.5237	1.5254	1.4718
MAPF-DBLMC-NC	1.8053	1.6523	1.6285	1.6954
MAPF-DBLMC-NMC	2.4031	2.1876	2.5077	2.3661
MPF-DBLMC	1.4181	1.5274	1.5490	1.4982

Similarly, choose the right- and left-end thresholds as $y_r^{i,s} = 12$ and $y_l^{i,s} = -12$ and keep other parameters unchanged. Based on Proposition 2 and Algorithm 1, the simulation results in relation to the saturation-like censoring model (5) are summarized in Figs. 9-15 and TABLE II, which

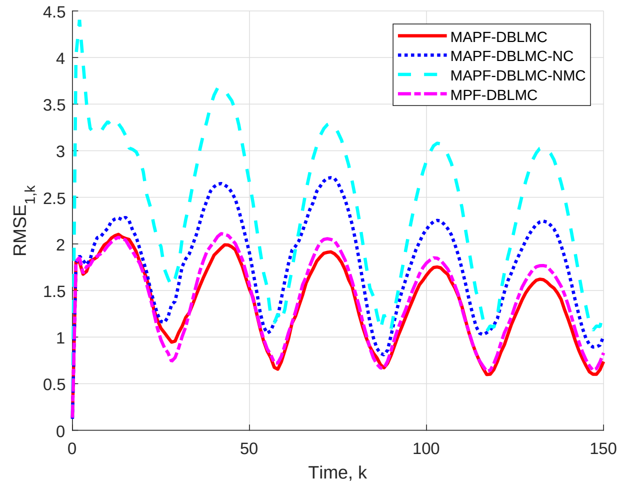

Fig. 6: RMSEs of different algorithms for target node 1.

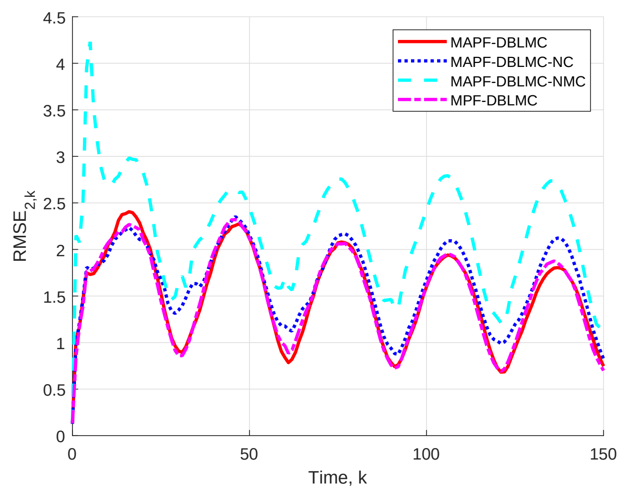

Fig. 7: RMSEs of different algorithms for target node 2.

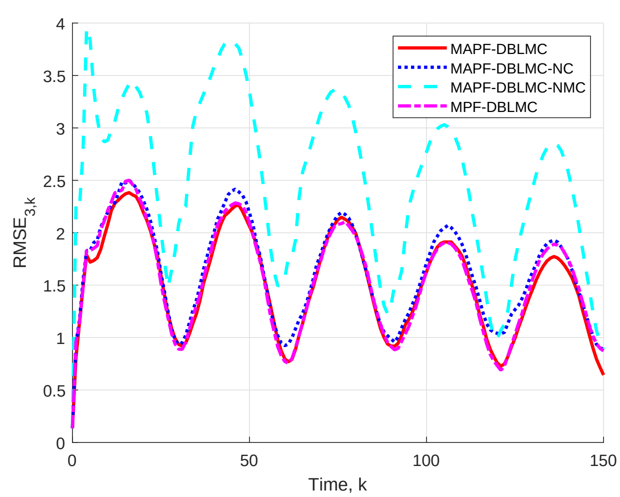

Fig. 8: RMSEs of different algorithms for target node 3.

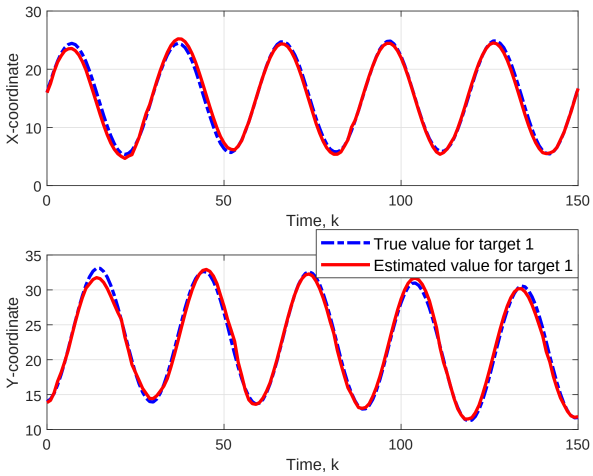

Fig. 9: True and estimated trajectories of target node 1.

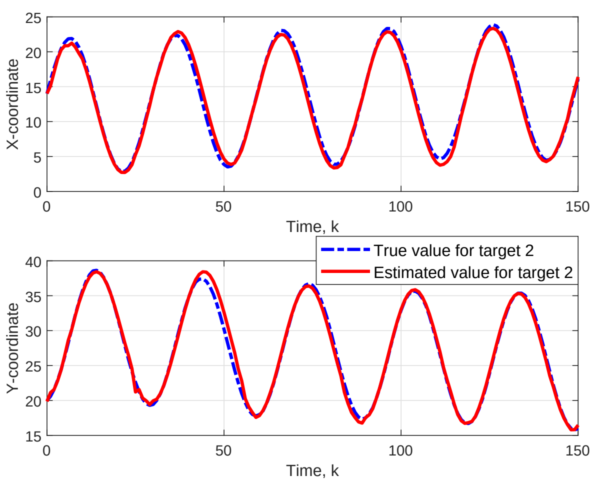

Fig. 10: True and estimated trajectories of target node 2.

demonstrate the effectiveness and usefulness of the proposed auxiliary particle filtering algorithm in the case of random access protocol and saturation-like measurement censoring (denoted as SLMC).

TABLE II: Average RMSEs of different algorithms with respect to saturation-like censoring.

	Target 1	Target 2	Target 3	Average
MAPF-SLMC	1.0308	1.1739	1.0746	1.0931
MAPF-SLMC-NC	1.1889	1.3841	1.5005	1.3578
MAPF-SLMC-NMC	7.7112	5.5404	5.9013	6.3843
MPF-SLMC	1.1966	1.1611	1.0942	1.1506

V. Conclusions

In this paper, the particle filtering problem has been discussed for a class of nonlinear/non-Gaussian CNs with on-off stochastic coupling and measurement censoring under

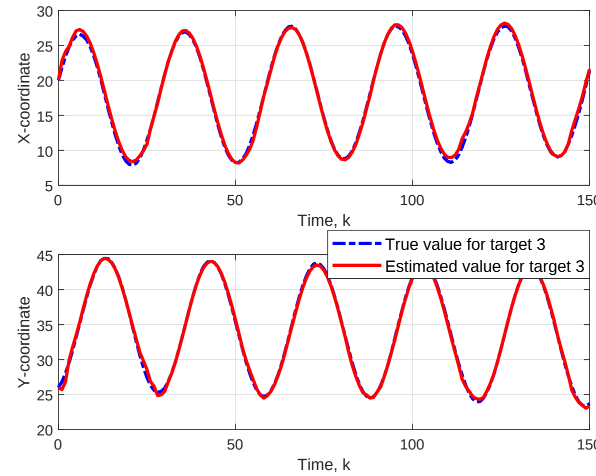

Fig. 11: True and estimated trajectories of target node 3.

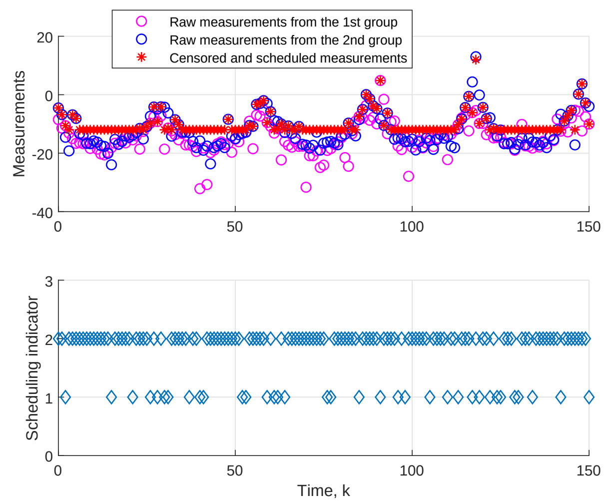

Fig. 12: The first measurement component associated with target node 1.

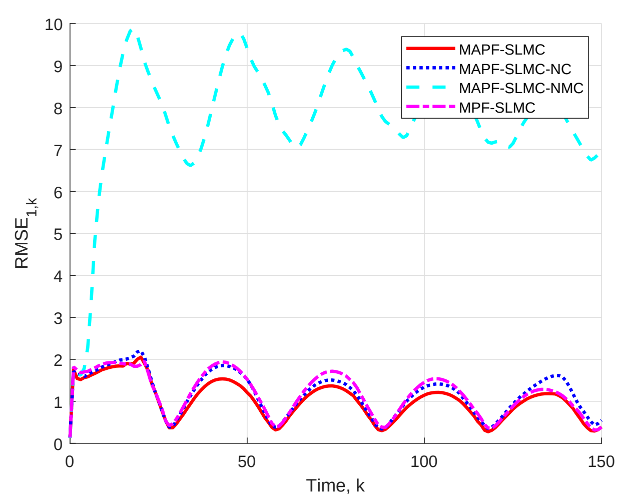

Fig. 13: RMSEs of different algorithms for target node 1.

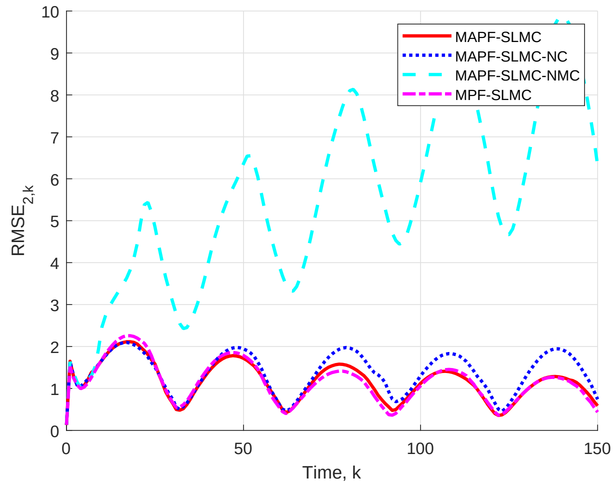

Fig. 14: RMSEs of different algorithms for target node 2.

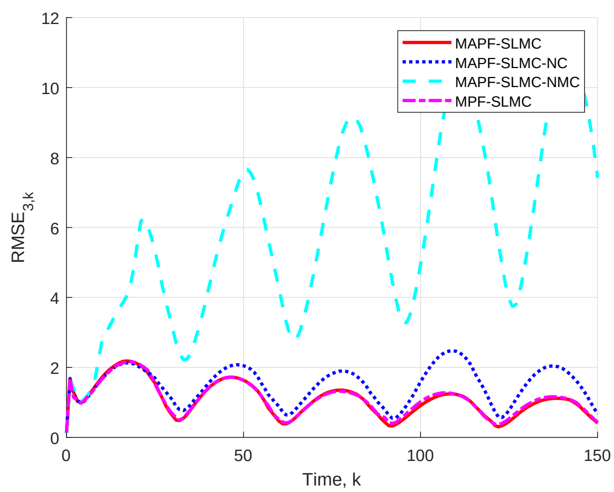

Fig. 15: RMSEs of different algorithms for target node 3.

the scheduling of random access protocol. A Bernoulli distributed random variable has been introduced to characterize the stochastic behaviors of on-off coupling, and the known statistical property has been utilized in the process of particle propagations. To model the scheduling rule of the random access protocol, an independent and identically distributed stochastic process has been adopted with known probability distribution. In addition, both the dead-band-like measurement censoring and saturation-like measurement censoring have been taken into consideration to flexibly reflect the different circumstances in practical engineering. Accordingly, two modified expressions of the likelihood function have been established to compensate the effects of protocol scheduling and measurement censoring in weight update. Finally, a multi-target tracking scenario with three interacted targets has been considered and the corresponding simulation results have been presented to elucidate the practical applicability and usefulness of the developed filtering scheme. An interesting yet challenging direction for future work would be establishing a rigorous theoretical framework for performance analysis.

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