

A Survey on Nonlinear Kalman Filtering under Communication Resource Constraints: Methods and Scheduling Strategies

Kai Lin, Yezheng Wang* and Fan Wang

College of Automation, Nanjing University of Information Science and Technology, Nanjing 211800, China

* Correspondence: wangyz_sdust@163.com

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Abstract: In practical engineering applications, systems governed by nonlinear dynamics are widespread, and their inherent complexity has made the study and development of high-performance filtering methods an important and active research topic. This issue becomes particularly prominent in networked control systems. By leveraging distributed sensing and cooperative operation, networked control systems can improve overall system performance; however, under networked communication environments, their distributed architectures and inherent resource limitations further increase the difficulty of nonlinear filter design. This paper presents a systematic review of resource-efficient nonlinear Kalman filtering for networked control systems. First, mainstream nonlinear Kalman filtering methods are classified, and the characteristics of typical communication resource constraints in networked environments are analyzed. Then, representative strategies for alleviating communication bottlenecks are summarized and examined, including event-triggered mechanisms, encoding-decoding schemes, and sensor scheduling mechanisms. On this basis, recent advances in nonlinear Kalman filtering methods that explicitly incorporate the aforementioned resource-aware mechanisms into the filter design process are reviewed. Furthermore, the interactions among different constraint-handling techniques are discussed, and their combined effects on filtering performance are evaluated. Finally, several open issues in this field are highlighted, such as security assurance under resource-constrained conditions and adaptability to time-varying network environments, and several promising directions for future research are outlined.

Keywords: resource constraints; network scheduling policies; nonlinear systems; Kalman filtering; networked control systems

1. Introduction

State estimation (SE) infers the internal state of a system by fusing noisy observations with prior information provided by a dynamic model. SE is of fundamental importance to a variety of critical tasks, such as high-precision control, fault diagnosis, and trajectory tracking. Over the past decades, SE has remained a major research focus and has been widely applied in numerous fields, including target tracking [1], aerospace navigation and guidance [2], power systems [3], autonomous driving [4], and environmental monitoring [5]. Since the introduction of the Kalman filter (KF) [6], recursive filtering has become a cornerstone methodology in the field of SE. Under appropriate linear Gaussian assumptions, through the recursive process of state prediction and measurement update, the filter is able to obtain the optimal state estimate at each time step using only the previous state estimate and the current measurement information. The theoretical optimality and high computational efficiency of KF enable it to effectively reconcile model predictions with sensor measurements in uncertain dynamic environments. Owing to these distinctive advantages, Kalman-filtering-based methods have remained a central topic in academic research over the past several decades and have been extensively adopted across a broad range of disciplines.

Although KF is optimal for linear Gaussian systems [6], most real-world engineering systems exhibit nonlinear dynamics, which substantially limits the practical applicability of the conventional KF. Specifically, when Gaussian distributions propagate through nonlinear transformations, the resulting probability density functions are generally distorted, thereby violating the fundamental assumptions on which the classical KF is established [7]. As a consequence, the classical KF is not directly applicable to state estimation problems in nonlinear systems. To overcome this limitation, various extensions of KF have been developed. Representative examples include the extended Kalman filter (EKF) [8], the unscented Kalman filter (UKF) [7], and the cubature Kalman filter (CKF) [9]. While preserving the recursive structure of the standard KF, these nonlinear filtering methods enable effective state estimation for nonlinear systems through techniques such as local linearization and deterministic sampling.

Networked control systems (NCSs) are gradually replacing traditional point-to-point hard-wired architectures in modern engineering applications, where system components exchange data over a shared communication network [10]. The adoption of a shared network not only significantly reduces wiring and maintenance costs but also improves system flexibility and reconfigurability. Owing to their capability for coordinated resource sharing, NCSs have been widely applied in many fields [11], thereby further promoting the development of state estimation techniques. Nevertheless, network-based communication also introduces distinctive challenges to state estimation. This is because inherent network imperfections undermine the real-time performance and determinism of data transmission [12]. These network-induced limitations directly affect the estimation accuracy and convergence performance of the state estimation process.

In a typical NCS, limited bandwidth and energy resources often make it difficult to support high-frequency or large-scale data transmission. Such constrained communication capability creates a significant mismatch between practical operating conditions and the ideal communication assumptions underlying traditional filtering algorithms. As the network scale continues to increase, shared channels become more prone to congestion, thereby giving rise to packet loss, out-of-order delivery, increased latency, and degraded data quality [13,14]. Accordingly, given the inherent constraints of NCSs in bandwidth, energy, and channel access, current research has gradually shifted from pursuing purely local optimal estimation to achieving an effective tradeoff between communication cost and global estimation accuracy.

Existing studies mainly provide three categories of solutions to address network bandwidth and energy constraints. The first category adopts event-triggered communication schemes, in which data are transmitted only when predefined triggering conditions are satisfied, thereby replacing the conventional periodic transmission mode. Although event-triggered strategies can effectively conserve communication resources, they also introduce complex issues such as nonuniform sampling and asynchrony [15,16]. The second category involves access scheduling protocols, which alleviate network congestion and data collisions through orderly allocation of channel resources. The key challenge lies in achieving a proper balance between the real-time requirements and fairness of individual nodes and the overall operational efficiency of the network [17,18]. The third category employs quantization and encoding-decoding techniques to compress packet sizes, thereby reducing the communication load. Nevertheless, the quantization process inevitably introduces quantization errors. Therefore, subsequent filtering algorithms should incorporate corresponding compensation mechanisms to mitigate the resulting degradation in estimation accuracy [19].

Driven by the widespread adoption of NCSs, SE technology has gradually evolved from classical centralized architectures to modern distributed paradigms. The distributed framework is mainly characterized by cooperative networking, decentralized processing, and distributed information fusion [20,21]. To meet the growing demand for large-scale cooperative SE, distributed Kalman filtering (DKF) schemes have been extensively studied. Early research on distributed filtering mainly focused on consensus-based strategies, where the globally optimal estimate is approximated through iterative information exchange among neighboring nodes [22,23]. Subsequently, to cope with stringent communication resource constraints, more advanced DKF algorithms have been proposed. These resource-efficient approaches incorporate mechanisms such as event-triggered transmission [16], encoding-decoding schemes [24], and asynchronous randomized communication [25]. In recent years, research efforts have further shifted toward the integrated co-design of communication scheduling and filtering, in which network scheduling rules are directly embedded into the system model to achieve joint optimization [26,27].

Nonlinear filtering continues to be a major research focus because of its significant engineering value and practical relevance. In recent years, several representative review articles have been published, covering topics such as recursive filtering, nonlinear estimation methods, and distributed filtering [17,28–30]. Nevertheless, the existing literature still lacks a systematic review of Kalman-like filtering methods for nonlinear NCSs that explicitly account for resource constraints. Compared with prior surveys, the main contributions of this work are threefold. First, recent advances in nonlinear KF under communication-constrained settings are systematically reviewed. Second, the latest results on KF performance analysis and scheduling strategies are surveyed, and the associated design challenges are discussed, thereby providing guidance for researchers and practitioners in selecting appropriate scheduling schemes

and filter types. Third, open challenges and promising research directions in this field are highlighted to guide future developments. Although not exhaustive, this review aims to present the latest progress and emerging trends in networked SE.

The remainder of this manuscript is organized as follows. Section 2 reviews widely used nonlinear Kalman filters, including the EKF, UKF, CKF, Maximum Correntropy Criterion Kalman Filter (MCKKF), Gaussian sum Kalman filter (GSKF) and Set-Membership Filter (SMF). It also outlines typical models of communication constraints, such as bandwidth limitations, energy constraints, and channel contention. Section 3 summarizes the major communication-resource management strategies, including event-triggered, deterministic, and stochastic scheduling, as well as encoding-decoding techniques. Section 4 synthesizes recent advances in nonlinear KF methods under the aforementioned scheduling mechanisms. Finally, Section 5 concludes the manuscript and highlights open challenges and future research directions. The overall organization of this review is illustrated in Figure 1.

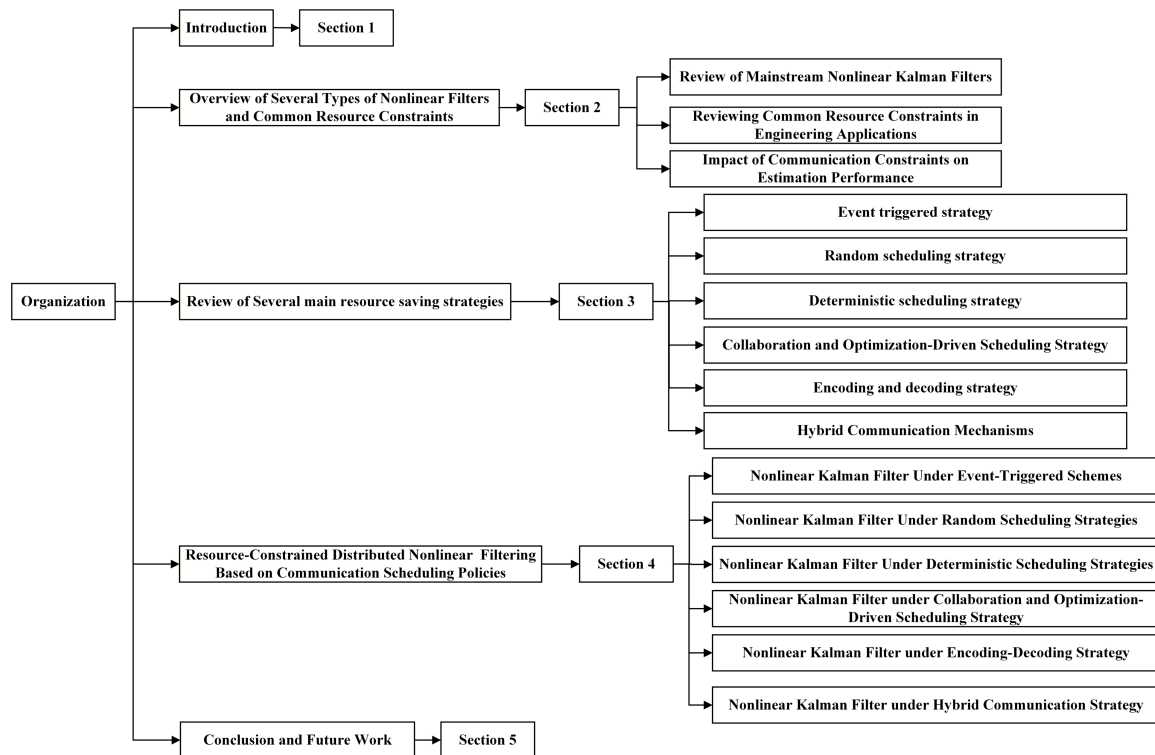


Figure 1. Organization of the survey.

2. Fundamentals and Problem Formulation of Filters for Networked Nonlinear Systems

In nonlinear NCSs, the SE process relies on the coordination of several distinct functional units, including spatially distributed sensor networks, resource-constrained communication channels, and centralized or distributed estimators. Figure 2 illustrates the overall architectural workflow, from measurement generation to the final state estimate.

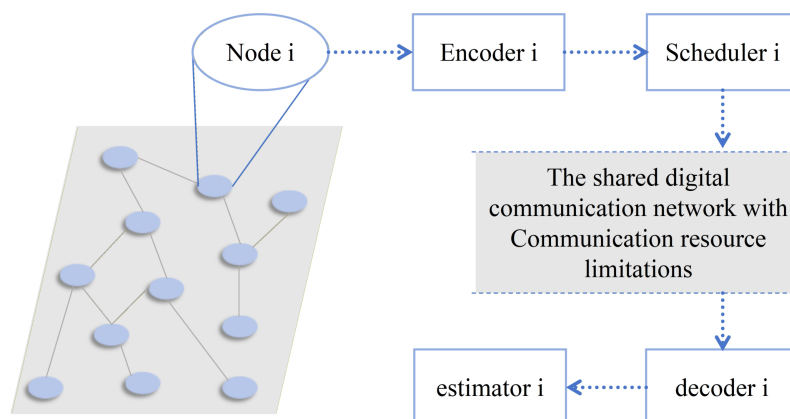


Figure 2. Networked structure.

As shown in Figure 2, a typical networked estimation architecture consists of several key components with different functions. Sensor nodes collect system measurements at certain sampling rates. The encoder then compresses the collected signals through quantization and coding. The scheduler determines the transmission timing and selects the transmitting nodes so as to reduce transmission frequency and minimize resource consumption. The encoded data packets are then sent to the receiver through the communication channel, where the decoder reconstructs the transmitted information and recovers the original statistical properties. Finally, the filter performs state estimation based on the decoded measurements.

2.1. Foundations of Filter for Nonlinear Systems

The current section introduces four categories of nonlinear KF algorithms for NCSs. The first category is the EKF, which is based on linearization techniques. The second category comprises the UKF and the CKF, which rely on deterministic sampling methods. The third category is the MCCKF, which employs the maximum correntropy criterion as the optimization criterion. The fourth category corresponds to set-membership-based filtering methods. Before detailing these methods, we first present a general formulation of nonlinear NCSs.

$$\begin{cases} \mathbf{x}_{k+1} = f_k(\mathbf{x}_k) + \mathbf{w}_k, \\ \mathbf{y}_{i,k} = h_{i,k}(\mathbf{x}_k) + \mathbf{v}_{i,k}, \end{cases} \quad (1)$$

where $\mathbf{x}_k \in \mathbb{R}^{n_x}$ denotes the system state to be estimated, $\mathbf{y}_{i,k} \in \mathbb{R}^{n_y}$ denotes the measurement output of the i -th sensor, and the subscript k represents the time index. Functions $f_k(\cdot) : \mathbb{R}^{n_x} \mapsto \mathbb{R}^{n_x}$ and $h_{i,k}(\cdot) : \mathbb{R}^{n_x} \mapsto \mathbb{R}^{n_y}$ denote the known nonlinear system transition and measurement functions, respectively. Variables $\mathbf{w}_k \in \mathbb{R}^{n_x}$ and $\mathbf{v}_{i,k} \in \mathbb{R}^{n_y}$ denote the process noise and the measurement noise of the i -th sensor, with probability densities $p_w(\cdot)$ and $p_{v_i}(\cdot)$, respectively. In Gaussian noise scenarios, the probability density functions $p_w(\cdot)$ and $p_{v_i}(\cdot)$ follow specific distributions typically defined as $\mathcal{N}(0, \mathbf{Q}_k)$ and $\mathcal{N}(0, \mathbf{R}_{i,k})$. The notation $\mathcal{N}(\mu, \Sigma)$ denotes a Gaussian density with mean μ and covariance Σ .

In an NCS, each node functions as a local estimator. This section introduces local filters tailored to distributed environments. The filtering methods reviewed in detail here include the EKF, CKF, MCCKF, and set-membership-based filtering methods. Within the deterministic sampling category, the CKF is presented as a representative method, while the UKF is not discussed separately. Each local filter processes data at the individual node level. The decentralized computation is performed prior to any global coordination or information fusion.

2.1.1. Nonlinear Kalman Filter Based on Local Linearization

The EKF extends the classical KF to accommodate nonlinear systems by relying on local linearization to handle nonlinear dynamics. This estimator is particularly effective when the system nonlinearity is moderate and the deviation from the linearization point remains small. Structurally, the EKF retains the recursive prediction and update phases of the standard KF, but approximates nonlinear functions using Jacobian matrices, thereby enabling the treatment of nonlinear dynamics and measurement models.

For completeness, the standard EKF recursion is briefly summarized. Given the previous estimate $\hat{\mathbf{x}}_{i,k-1|k-1}$ and covariance $\mathbf{P}_{i,k-1|k-1}$, the prediction and update steps are given by

$$\begin{cases} \hat{\mathbf{x}}_{i,k|k-1} = f_{k-1}(\hat{\mathbf{x}}_{i,k-1|k-1}), \\ \mathbf{P}_{i,k|k-1} = \mathbf{F}_{i,k-1} \mathbf{P}_{i,k-1|k-1} \mathbf{F}_{i,k-1}^T + \mathbf{Q}_{k-1}, \end{cases} \quad (2)$$

and

$$\begin{cases} \mathbf{K}_{i,k} = \mathbf{P}_{i,k|k-1} \mathbf{H}_{i,k}^T (\mathbf{H}_{i,k} \mathbf{P}_{i,k|k-1} \mathbf{H}_{i,k}^T + \mathbf{R}_{i,k})^{-1}, \\ \hat{\mathbf{x}}_{i,k|k} = \hat{\mathbf{x}}_{i,k|k-1} + \mathbf{K}_{i,k} (\mathbf{y}_{i,k} - h_{i,k}(\hat{\mathbf{x}}_{i,k|k-1})), \\ \mathbf{P}_{i,k|k} = (\mathbf{I} - \mathbf{K}_{i,k} \mathbf{H}_{i,k}) \mathbf{P}_{i,k|k-1} (\mathbf{I} - \mathbf{K}_{i,k} \mathbf{H}_{i,k})^T \\ \quad + \mathbf{K}_{i,k} \mathbf{R}_{i,k} \mathbf{K}_{i,k}^T, \end{cases} \quad (3)$$

where $\mathbf{F}_{i,k-1}$ and $\mathbf{H}_{i,k}$ are the Jacobian matrices of the state and measurement functions, respectively.

Numerous EKF variants have been developed to address specific technical challenges. The main motivations include mitigating first-order linearization errors under strong nonlinearities, handling complex or nondifferentiable models for which analytical Jacobians are unavailable, and accommodating non-Gaussian noise. Since these extensions are beyond the scope of this paper, interested readers are referred to the relevant literature for further details [31,32].

2.1.2. Deterministic-Sampling-Based Nonlinear Kalman Filter

Nonlinear Kalman filters based on deterministic sampling mainly include the UKF and the CKF. The UKF employs the unscented transform to avoid linearizing the system model. In contrast, the CKF uses the spherical-radial cubature rule to approximate Gaussian-weighted integrals. Although the UKF and CKF adopt different sampling rules, they share the same basic characteristics. For example, the CKF can be regarded as a special case of the standard UKF with the scaling parameter set to zero [33]. Likewise, the UKF is formally equivalent to a sparse-grid quadrature filter with precision level 2 [34]. Given these close theoretical connections, this paper focuses on the CKF for detailed illustration.

For completeness, the standard CKF recursion is briefly summarized. Given the posterior estimate $\hat{\mathbf{x}}_{i,k-1|k-1}$ and covariance $\mathbf{P}_{i,k-1|k-1}$, $2n_x$ cubature points are generated and propagated through the nonlinear functions $f_{k-1}(\cdot)$ and $h_{i,k}(\cdot)$. The predicted state and covariance are obtained as

$$\begin{cases} \hat{\mathbf{x}}_{i,k|k-1} = \frac{1}{2n_x} \sum_{l=1}^{2n_x} \mathbf{x}_{il,k|k-1}, \\ \mathbf{P}_{i,k|k-1} = \frac{1}{2n_x} \sum_{l=1}^{2n_x} \tilde{\mathbf{x}}_{il,k|k-1} \tilde{\mathbf{x}}_{il,k|k-1}^T + \mathbf{Q}_{k-1}, \end{cases} \quad (4)$$

where $\tilde{\mathbf{x}}_{il,k|k-1} = \mathbf{x}_{il,k|k-1} - \hat{\mathbf{x}}_{i,k|k-1}$, and $\mathbf{x}_{il,k|k-1} = f_{k-1}(\mathbf{x}_{il,k-1|k-1})$ denotes the propagated cubature points.

The measurement update is performed by computing the predicted measurement, innovation covariance, and cross-covariance:

$$\begin{cases} \hat{\mathbf{y}}_{i,k|k-1} = \frac{1}{2n_x} \sum_{l=1}^{2n_x} \mathbf{y}_{il,k|k-1}, \\ \mathbf{P}_{zz,k}^i = \frac{1}{2n_x} \sum_{l=1}^{2n_x} \tilde{\mathbf{y}}_{il,k|k-1} \tilde{\mathbf{y}}_{il,k|k-1}^T + \mathbf{R}_{i,k}, \\ \mathbf{P}_{xz,k}^i = \frac{1}{2n_x} \sum_{l=1}^{2n_x} \tilde{\mathbf{x}}_{il,k|k-1} \tilde{\mathbf{y}}_{il,k|k-1}^T, \end{cases} \quad (5)$$

where $\tilde{\mathbf{y}}_{il,k|k-1} = \mathbf{y}_{il,k|k-1} - \hat{\mathbf{y}}_{i,k|k-1}$ and $\mathbf{y}_{il,k|k-1} = h_{i,k}(\mathbf{x}_{il,k|k-1})$. Then, the state estimate and covariance are updated by

$$\begin{cases} \mathbf{K}_{i,k} = \mathbf{P}_{xz,k}^i (\mathbf{P}_{zz,k}^i)^{-1}, \\ \hat{\mathbf{x}}_{i,k|k} = \hat{\mathbf{x}}_{i,k|k-1} + \mathbf{K}_{i,k} (\mathbf{y}_{i,k} - \hat{\mathbf{y}}_{i,k|k-1}), \\ \mathbf{P}_{i,k|k} = \mathbf{P}_{i,k|k-1} - \mathbf{K}_{i,k} \mathbf{P}_{zz,k}^i \mathbf{K}_{i,k}^T. \end{cases} \quad (6)$$

Beyond the UKF and CKF, researchers have developed other deterministic sampling-based filters. Notable variants include the Gaussian-Hermite quadrature filter, which is based on Gauss-Hermite quadrature rules [35], and the sparse grid quadrature filter, which employs sparse-grid techniques [34]. These algorithms provide alternative numerical integration approaches for nonlinear SE.

2.1.3. Nonlinear Kalman Filter Based on Maximum Correntropy Criterion and Gaussian Mixture

The MCCKF has emerged as an effective technique for non-Gaussian environments. It is discussed separately in this paper because it replaces the traditional minimum mean-square error criterion in the Kalman filtering framework with correntropy as the local optimality criterion [36,37]. By adopting the correntropy criterion, the MCCKF offers a distinct advantage in handling non-Gaussian noise, such as impulsive or heavy-tailed noise. In terms of structure, the MCCKF retains the basic prediction-update framework of the standard Kalman filter. However, in the update step, the objective is no longer to minimize the mean-square error of state estimation. Instead, the optimal estimate is obtained by maximizing correntropy.

The prediction step of the MCCKF depends on the underlying nonlinear filtering method. For example, an EKF-based formulation uses a linearization-based prediction, whereas UKF-based and CKF-based formulations use unscented and cubature transformations, respectively, to compute the predicted state estimate and covariance. In the update step, the local state estimate $\mathbf{x}_{i,k}$ is obtained by optimizing the following cost function [38,39]:

$$J(\mathbf{x}_{i,k}) = G_\sigma(\|\mathbf{x}_{i,k} - \hat{\mathbf{x}}_{i,k|k-1}\|_{\mathbf{P}_{i,k|k-1}^{-1}}) + G_\sigma(\|\mathbf{y}_{i,k} - h_{i,k}(\mathbf{x}_{i,k})\|_{\mathbf{R}_{i,k}^{-1}}). \quad (7)$$

where $\|\mathbf{a}\|_{\mathbf{M}} \triangleq (\mathbf{a}^T \mathbf{M} \mathbf{a})^{1/2}$ for a symmetric positive-definite weighting matrix $\mathbf{M}$, and $G_\sigma(s) = \exp(-s^2/(2\sigma^2))$ with $\sigma > 0$. The weighting matrices are $\mathbf{P}_{i,k|k-1}^{-1}$ and $\mathbf{R}_{i,k}^{-1}$, where both covariance matrices are assumed to be positive definite.

With the Gaussian kernel function $G_\sigma(e) = \exp(-\frac{e^2}{2\sigma^2})$, the error e is mapped into the interval $(0, 1]$, enabling correntropy to capture information from all even-order moments of e . As the magnitude of the error increases, the kernel value decreases accordingly. Under the maximum correntropy criterion, the asymptotic decay of the Gaussian kernel suppresses the influence of large errors, particularly outliers, which typically correspond to observations with large residuals. It is worth noting that when the kernel width σ of the Gaussian kernel tends to infinity, the estimator reduces to the standard Kalman filter [38]. Compared with the EKF, UKF, and CKF, the iterative solution procedure of the MCKKF incurs a higher computational cost, which may limit its applicability in real-time systems. In addition, the kernel width σ is a key parameter that strongly affects performance and should therefore be selected carefully according to the requirements of the specific application [40].

The GSKF is another important approach for handling non-Gaussian noise. It is based on the principle that any non-Gaussian probability density function can be approximated by a weighted sum of multiple Gaussian densities [41–43]. The algorithm typically proceeds in three steps. First, the initial non-Gaussian distribution is approximated by a sum of Gaussian components. Second, a bank of parallel Kalman filters is used to update each Gaussian component individually. Third, the component weights are updated according to the measurement likelihood. Notably, a major drawback of this mixture approximation is the exponential growth in the number of Gaussian components over time. This growth results in prohibitive computational complexity. Therefore, researchers commonly employ component merging or resampling strategies to constrain the number of components. The specific reduction algorithm used for component merging has a significant impact on filter performance. For further details, readers are referred to [44].

2.1.4. Set-Membership Filtering for Nonlinear Systems

Bayesian nonlinear filtering methods typically require accurate probabilistic descriptions of system uncertainties. However, in practical NCSs, uncertainties arising from disturbances, model mismatches, and communication constraints may not satisfy known statistical assumptions. Set-membership estimation provides an alternative framework by describing uncertainties as bounded sets and guaranteeing that the true state remains within the estimated region [45]. Among various set representations, including ellipsoids, polytopes, and zonotopes, zonotopes have gained increasing attention due to their computational efficiency and flexibility in representing complex uncertainties [46,47]. Recently, the combination of zonotopic representations with recursive filtering has emerged as an effective approach for robust state estimation under communication-constrained environments.

Specifically, an n -dimensional zonotope is defined as

$$\mathbf{Z} = \langle \mathbf{c}, \mathbf{G} \rangle = \{\mathbf{c} + \mathbf{G}\boldsymbol{\xi} \mid \|\boldsymbol{\xi}\|_\infty \leq 1\}, \quad (8)$$

where $\mathbf{c}$ and $\mathbf{G}$ denote the center vector and generator matrix, respectively. Unlike probabilistic filters, zonotopic filters characterize uncertainties by bounded sets and recursively propagate the state region according to system dynamics and measurement constraints. For nonlinear systems, the predicted state set is obtained by an outer approximation of the nonlinear mapping:

$$\mathbf{Z}_{i,k+1|k} \supseteq f_k(\mathbf{Z}_{i,k|k}) \oplus \mathbf{W}, \quad (9)$$

where $\mathbf{W}$ denotes the bounded process noise set and $\oplus$ represents the Minkowski sum. During the measurement update, the state estimate is further constrained by the measurement consistency set:

$$\mathbf{Z}_{i,k+1|k+1} = \text{Outer}_Z(\mathbf{Z}_{i,k+1|k} \cap \mathcal{X}_{i,k+1}), \quad (10)$$

where $\mathcal{X}_{i,k+1}$ denotes the set of states consistent with the received measurement at time $k+1$ under the bounded measurement noise, and $\text{Outer}_Z(\mathcal{S})$ denotes a zonotopic outer approximation satisfying $\mathcal{S} \subseteq \text{Outer}_Z(\mathcal{S})$.

The performance of zonotopic filtering is mainly influenced by the correction gain, uncertainty bounds, generator matrix, and outer approximation strategy. The gain and approximation strategy determine the tightness of

the updated set, while the generator matrix affects the trade-off between estimation accuracy and computational complexity. Specifically, as the number of generators increases during recursive prediction and measurement updates, the generator matrix becomes progressively enlarged, leading to higher memory consumption and computational complexity. Therefore, generator reduction techniques are usually required to maintain computational tractability, especially in severely resource-constrained networks [48]. Meanwhile, accurate uncertainty characterization is essential to guarantee state inclusion; overly conservative bounds degrade accuracy, whereas underestimated bounds may violate the inclusion property. Therefore, zonotopic filtering aims to balance estimation accuracy, robustness, and computational efficiency.

Remark 1. In nonlinear NCSs, individual nodes can access only local nonlinear measurements, and each computing unit performs nonlinear approximation solely on the basis of its own local estimate. Such decentralized operation often gives rise to inconsistencies in higher-order information across different nodes. To mitigate the resulting estimation bias, each node typically exchanges and fuses information matrices and vectors after completing local nonlinear filtering. This fusion process is realized through protocols such as diffusion strategies and consensus iterations. Through this mechanism, the network can integrate local measurement information from different nodes while implicitly coordinating the local approximation results of the nonlinear model across the entire nonlinear NCS. Consequently, the system can converge to a global estimate that exceeds the capability of any individual node operating in isolation.

2.2. Modeling of Resource Constraints

For NCSs, channel capacity imposes an upper bound on throughput, making bandwidth limitation one of the fundamental constraints of NCSs [17,49,50]. In addition to bandwidth limitations, energy constraints also constitute a fundamental challenge in NCSs. Wireless transmission depletes the limited energy reserves of sensors [21]. Moreover, shared channels require strict access control to prevent data conflicts caused by simultaneous transmissions [51]. Bandwidth limitation, energy constraints, and channel contention together define the core requirements of system design. Therefore, the following discussion focuses on these three aspects: bandwidth limitation, energy constraint, and channel contention.

2.2.1. Bandwidth Limitations

In NCSs, bandwidth constraints are commonly modeled as bit-rate limits. Assume that the continuous-valued measurement $\mathbf{y}_{i,k}$ from sensor i is quantized by $Q(\cdot)$ and represented by a vector of quantization indices $\mathbf{b}_i = [b_{i1}, b_{i2}, \dots, b_{i n_y}]$, where $b_{ij} \in \{0, 1, \dots, q_i - 1\}$. When each measurement component is quantized into q_i levels and independently encoded using a fixed-length binary code, the measurement payload requires $n_y \lceil \log_2 q_i \rceil$ bits per sampling instant, which reduces to $n_y \log_2 q_i$ when q_i is a power of two. Let R_i denote the bit rate allocated to sensor i . For a given sampling rate, this allocation constrains the achievable quantization resolution. If R denotes the total available bit rate of the NCS, the allocations must satisfy [52]:

$$\sum_{i=1}^N R_i \leq R. \quad (11)$$

2.2.2. Energy Constraints

Whereas bandwidth limitations primarily affect estimation performance, energy limitations directly determine the operational lifetime and overall viability of the system [53,54]. In general, the total energy consumption of a node consists of three distinct components: sensing, data processing, and wireless communication. Among these functions, data transmission typically dominates the energy budget. Accordingly, research efforts have focused on mechanisms for reducing communication energy consumption [53,55,56]. Assuming the transmission of l bits of data to a receiver at distance d , the energy consumption of the sending node $E_{Tx}(l, d)$ and that of the receiving node $E_{Rx}(l)$ are modeled as follows [57,58]:

$$\begin{cases} E_{Tx}(l, d) = \underbrace{E_{\text{elec}} \cdot l}_{\text{Circuit loss}} + \underbrace{\epsilon_{\text{amp}} \cdot l \cdot d^\alpha}_{\text{Power amplification loss}}, \\ E_{Rx}(l) = E_{\text{elec}} \cdot l, \end{cases} \quad (12)$$

where E_{elec} represents the energy consumption per bit processed by the transceiver circuit, and ϵ_{amp} denotes the power amplifier gain factor. $E_{Tx}(l, d)$ represents the total energy consumed by a node to transmit an l -bit packet

over a distance d , while $E_{Rx}(l)$ denotes the energy required to receive the same packet. The parameter α is the path loss exponent, which typically takes a value of $\alpha = 2$ (free-space model for short distances) or $\alpha = 4$ (multipath fading model for long distances). In a finite-energy budget model, node i is usually assumed to have an initial energy $E_{i,T}$. The corresponding total transmission-energy constraint over the time interval $[0, K]$ is formulated as follows:

$$\sum_{k=0}^K \gamma_{i,k} \cdot E_{i,p} \leq E_{i,T}, \quad (13)$$

where $\gamma_{i,k} \in \{0, 1\}$ is the scheduling decision variable (1 indicates transmission, 0 indicates silence) and $E_{i,p}$ denotes the average energy required to transmit one measurement.

2.2.3. Medium Access Constraints

In networked filtering, channel contention can significantly degrade system performance. Because the shared medium permits only limited simultaneous access, uncoordinated concurrent transmissions may lead to data collisions. Such collisions can cause transmission failures, resulting not only in packet losses but also in random transmission delays.

In NCSs, channel contention is usually not modeled directly; instead, researchers characterize its induced effects. The modeling process should also account for the specific features of the network. When contention events are temporally independent, a Bernoulli model is suitable for characterizing channel contention [59]. Otherwise, a Markov model is more appropriate [60,61]. From the perspective of the outcomes caused by channel contention, if data is discarded immediately after a contention failure, channel contention can be modeled as a packet loss process. If waiting and retransmission are permitted after a contention failure, a delay model or a queue model is appropriate [62–65]. In addition, channel-access models should distinguish between time division multiple access (TDMA) and carrier sense multiple access (CSMA) [66]. TDMA provides contention-free access through assigned time slots and, under a fixed slot allocation, can be represented by a deterministic scheduling sequence. CSMA uses contention-based access, whose outcomes can be represented by a stochastic access process that accounts for carrier sensing and random backoff [67]. Channel contention is a common communication constraint in NCSs with contention-based access. Therefore, filter design under channel contention remains an active and evolving research topic.

2.3. Impact of Communication Constraints on Estimation Performance

Although the nonlinear filtering methods introduced in Section 2.1 can effectively estimate system states under ideal communication conditions, practical NCSs are inevitably affected by communication constraints. These constraints introduce additional uncertainties and may alter the information update mechanism, thereby affecting the innovation covariance, estimation error covariance, and filter gain. This Section briefly analyzes the impacts of communication constraints on the filtering process from several perspectives. It should be noted that, due to the diversity and complexity of practical network constraints and their combinations, the following discussion cannot cover all possible cases.

2.3.1. Impact of Stochastic Scheduling Variables

Assume that $\gamma_{i,k} \in \{0, 1\}$ denotes a stochastic scheduling variable, where $\gamma_{i,k} = 0$ indicates that the information from sensor i is not transmitted, while $\gamma_{i,k} = 1$ indicates successful transmission. As introduced in Section 2.1, conventional filtering methods recursively compute the filter gain and estimation error covariance under ideal communication conditions. Let $\hat{P}_{i,k|k}(\gamma_{i,k})$ denote the estimation error covariance affected by the stochastic scheduling variable. It is clear that the scheduling variable directly influences the covariance update process, which can be expressed as $\hat{P}_{i,k|k}(\gamma_{i,k}) = P_{i,k|k-1} - \gamma_{i,k} K_{i,k} P_{zz,k}^i K_{i,k}^T$. When $\gamma_{i,k} = 0$, the measurement information is unavailable for updating the state estimate, and thus $\hat{P}_{i,k|k}(\gamma_{i,k}) \neq P_{i,k|k}$. Therefore, the stochastic scheduling variable transforms the deterministic Riccati recursion into a stochastic Riccati recursion [68].

2.3.2. Impact of Quantization and Encoding-Decoding Errors

Assume that the quantized measurement is given by $\hat{y}_{i,k} = Q(y_{i,k})$, which can be expressed as $\hat{y}_{i,k} = y_{i,k} + e_{i,k}$, where $e_{i,k}$ denotes the quantization error. Since the quantization error changes the statistical properties of the innovation term, the innovation covariance becomes $\hat{P}_{zz,k}^i \neq P_{zz,k}^i$, which further leads to a different filter gain $\hat{K}_{i,k} \neq K_{i,k}$. Therefore, quantization and encoding-decoding errors directly affect the computation of the filter gain and subsequently alter the recursive update of the estimation error covariance.

2.3.3. Impact of Non-Gaussian Uncertainties

Assume that the measurement noise does not follow a Gaussian distribution, i.e., $\mathbf{v}_{i,k} \not\sim \mathcal{N}(0, \mathbf{R}_{i,k})$, but is characterized by the mixture distribution $p(\mathbf{v}_{i,k}) = (1 - \varepsilon)\mathcal{N}(0, \mathbf{R}_{i,k}) + \varepsilon p(v)$, where $p(v)$ represents the non-Gaussian noise component. In the presence of non-Gaussian uncertainties, second-order statistics generally do not fully characterize the error distribution. However, non-Gaussianity alone does not imply an innovation covariance mismatch. Such a mismatch may arise when the noise statistics or prediction approximations used by the filter do not accurately represent the corresponding true moments. Conventional Kalman filtering methods based on Gaussian assumptions may therefore exhibit degraded performance under model mismatch or contamination by outliers [69]. Filtering approaches based on the maximum correntropy criterion or Gaussian-mixture representations can improve robustness or distributional approximation, depending on the noise characteristics and filter design.

3. Scheduling Strategies under Constrained Communication Resources

The central challenge of networked filtering is to manage data transmission under limited network resources while ensuring the desired filtering performance. To this end, a variety of resource-efficient strategies have been developed to mitigate resource constraints. Existing approaches mainly address three questions: which nodes should transmit, when transmission should be triggered, and what type of data should be exchanged. The overall objective is to minimize bandwidth usage and energy consumption while preserving estimation accuracy and system stability, thereby ensuring reliable and sustainable long-term operation in resource-constrained environments.

3.1. Event-Triggered Communication Strategies

Event-triggered strategies (ETs) determine whether to transmit data using information-dependent triggering rules, thereby reducing unnecessary communication and associated energy consumption. Based on how transmission decisions are made, these strategies can be distinguished as deterministic or randomized. Within deterministic event-triggered strategies, static event-triggered strategies (SETs) use triggering rules without an additional internal dynamic variable, whereas dynamic event-triggered strategies (DETs) incorporate such a variable into the triggering mechanism. Randomized event-triggered strategies (RETs), also referred to here as stochastic event-triggered strategies, introduce randomization into transmission decisions through information-dependent transmission probabilities. Here, the letter R denotes randomized. The static/dynamic distinction concerns the internal structure of the triggering mechanism and can also apply to randomized designs.

SETs employ a time-invariant threshold δ_i , whose main advantages are design simplicity and low computational overhead [70–72]. However, a fixed threshold lacks the flexibility to adapt to variations in system dynamics. If the threshold is set too low, unnecessary transmissions may occur during steady-state operation; if it is set too high, significant transient dynamics may not be captured, thereby degrading estimation performance. In contrast to SETs, DETs incorporate a time-varying auxiliary variable into the triggering condition [73,74]. This variable evolves dynamically and effectively exploits the communication resources saved at previous instants to regulate instantaneous transmissions. Unlike deterministic event-triggered strategies that rely on predefined thresholds, stochastic event-triggered mechanisms determine whether measurements are transmitted according to probabilistic rules [75,76]. The key idea is to introduce a random triggering variable whose probability distribution is adaptively designed based on innovation information. By appropriately designing the triggering probability, stochastic event-triggered mechanisms can reduce communication costs while preserving the tractability of the posterior distribution, making them an active research topic in recent years.

In Table 1, we summarize several representative event-triggering mechanisms. The notations used in the table are defined as follows: $\mathbf{r}_{i,k} = \mathbf{y}_{i,k} - \hat{\mathbf{y}}_{i,k}$ denotes the measurement innovation, $\mathbf{y}_{i,k}$ and $\hat{\mathbf{y}}_{i,k}$ are the actual and predicted measurements, respectively. $\mathbf{P}_{i,k|k-1}$ represents the predicted error covariance matrix. The parameters δ_i , θ , σ , σ_1 , σ_2 , and σ_3 are predefined triggering parameters, while $\eta_{i,k}$ denotes the auxiliary dynamic variable. The binary variable $\gamma_{i,k}$ indicates the transmission decision, and $\lambda_{i,k}$ represents the corresponding transmission probability. The indices k and s_t denote the current sampling instant and the latest transmission time, respectively.

Table 1. Representative event-triggered mechanisms.

Category	Mechanism	Triggering Condition	Characteristics
SETs	Absolute error threshold	$\bar{h}(\mathbf{r}_{i,k}, \delta_i) = \mathbf{r}_{i,k}^T \mathbf{r}_{i,k} - \delta_i$, $s_{t+1} = \inf\{k > s_t \bar{h}(\mathbf{r}_{i,k}, \delta_i) \geq 0\}$	Simple design and low computational cost, but lacks adaptability to dynamic variations.
	Relative error threshold	$\bar{h}(\mathbf{r}_{i,k}, \delta_i) = \mathbf{r}_{i,k}^T \mathbf{r}_{i,k} - \delta_i \mathbf{y}_{i,k}^T \mathbf{y}_{i,k}$, $s_{t+1} = \inf\{k > s_t \bar{h}(\mathbf{r}_{i,k}, \delta_i) \geq 0\}$	Improves adaptability to signal amplitude variations, but may suffer from zero-measurement problems.
DETSs	Auxiliary dynamic variable	$\bar{h}(\mathbf{r}_{i,k}, \eta_{i,k}) = \frac{1}{\theta} \ \mathbf{r}_{i,k}\ ^2 - \sigma \ \mathbf{y}_{i,k}\ ^2 + \eta_{i,k}$, $s_{t+1} = \inf\{k > s_t \bar{h}(\cdot) \geq 0\}$	Introduces an adaptive variable to exploit historical communication savings.
	Time-decay threshold	$\bar{h}(\mathbf{r}_{i,k}, k) = \mathbf{r}_{i,k}^T \mathbf{r}_{i,k} - (\sigma_1 e^{-\sigma_2 k} + \sigma_3)$, $s_{t+1} = \inf\{k > s_t \bar{h}(\mathbf{r}_{i,k}, k) \geq 0\}$	Gradually decreases the threshold to balance communication saving and estimation accuracy.
	Covariance-based threshold	$\bar{h}(\mathbf{r}_{i,k}, \delta_i) = \mathbf{r}_{i,k}^T \mathbf{r}_{i,k} - \delta_i \text{Tr}(\mathbf{P}_{i,k k-1})$, $s_{t+1} = \inf\{k > s_t \bar{h}(\mathbf{r}_{i,k}, \delta_i) \geq 0\}$	Adjusts transmission according to real-time estimation uncertainty.
RETSs	Probabilistic triggering	$\gamma_{i,k} \sim \text{Bernoulli}(\lambda_{i,k})$, $\lambda_{i,k} = \Pr(\gamma_{i,k} = 1 \mathbf{r}_{i,k})$	Determines transmission probabilistically and reduces communication burden while preserving estimation performance.

Recently, hybrid event-triggering mechanisms have attracted considerable research interest. Representative designs include periodic event-triggered schemes [77–79], quantized event-triggered schemes [80,81], and predictive event-triggered schemes [82]. Periodic event triggering effectively bridges the gap between time-triggered and event-triggered schemes. Under the discrete monitoring framework, the system evaluates the triggering condition at discrete sampling instants, such that data transmission occurs only when the condition is satisfied at the prescribed checking instants. Quantized event-triggering mechanisms explicitly incorporate quantization errors into the triggering condition, so that a node transmits data only when the quantization-induced deviation exceeds a preset threshold. Predictive event-triggering mechanisms use the system model to predict future states and determine whether transmission should be triggered on the basis of the prediction error, thereby further reducing the communication frequency.

Remark 2. From a practical perspective, deterministic event-triggered networked filtering can produce non-Gaussian conditional distributions even under Gaussian modeling assumptions. Consider specifically the absolute-error trigger in Table 1, and assume that the receiver can distinguish non-transmission from packet loss and knows the predicted measurement used by the trigger. When no transmission is triggered, the current measurement satisfies $\|\mathbf{y}_{i,k} - \hat{\mathbf{y}}_{i,k}\|^2 < \delta_i$, and therefore lies within the $\sqrt{\delta_i}$ -neighborhood of the predicted value. If the measurement distribution conditional on the prior information is Gaussian, conditioning additionally on this non-transmission event yields a truncated Gaussian measurement distribution. The resulting conditional posterior distribution of the state $\mathbf{x}_{i,k}$ is generally non-Gaussian. To maintain computational tractability, this state posterior can be approximated by a Gaussian distribution, for example through moment matching. For linear Gaussian systems, appropriately designed RETs can preserve the Gaussian form of the conditional state posterior. For general nonlinear systems, however, Gaussian approximations may still be required.

3.2. Random Scheduling Strategies

In NCSs, random scheduling (RS) is one of the important strategies for conserving communication resources [83–87]. The RS strategy offers clear advantages for distributed systems, particularly in terms of low implementation cost and strong robustness against network uncertainty. Since the RS strategy allocates channel access through a probabilistic mechanism, the transmission outcome becomes a random event. In the existing literature, the underlying random process is usually characterized by two main frameworks, namely, the Bernoulli process and the Markov chain.

(1) Bernoulli Random Access Model: The Bernoulli random access model is the simplest and most basic modeling framework, and it is usually used as a theoretical model for performance analysis and protocol design. At each time step k , sensor i attempts to transmit data to the central filter with a fixed probability p_i . Crucially, the stochastic trial is statistically independent of other sensors and historical transmission outcomes. Consequently, the

scheduling indicator variable $\gamma_{i,k}$ is governed by a Bernoulli distribution:

$$\gamma_{i,k} \sim \text{Bernoulli}(p_i), \quad (14)$$

where $P(\gamma_{i,k} = 1) = p_i$ and $P(\gamma_{i,k} = 0) = 1 - p_i$. Since each sensor transmits independently, scenarios may arise where no sensor transmits ($\sum_{i=1}^N \gamma_{i,k} = 0$) or multiple sensors transmit simultaneously ($\sum_{i=1}^N \gamma_{i,k} > 1$). In filtering models, it is typically assumed that data is lost when collisions occur.

(2) Markov Random Access Model: In contrast to the memoryless Bernoulli model, the Markov random access model allows the current access status to depend on the preceding status. Specifically, the scheduling indicator $\gamma_k \in \{0, 1\}$ is modeled as a time-homogeneous discrete-time Markov chain, where $\gamma_k = 1$ indicates that channel access is granted at time k , and $\gamma_k = 0$ indicates that it is not granted. The transition probability matrix is $\mathbf{P} = [p_{ij}]_{i,j \in \{0,1\}}$, with

$$\begin{aligned} p_{ij} &= \Pr\{\gamma_{k+1} = j \mid \gamma_k = i\}, \\ p_{ij} &\geq 0, \quad \sum_{j=0}^1 p_{ij} = 1, \quad i \in \{0, 1\}. \end{aligned} \quad (15)$$

Here, γ_k describes the binary channel-access status, whereas S_k , used later for RR/TOD scheduling, identifies the selected sensor.

Remark 3. Under RS protocols, the introduction of uncertain parameters renders the difference Riccati equation stochastic. Consequently, the evolution of the error covariance becomes a stochastic process. For nonlinear systems, stability analysis is particularly intricate because the convergence assessment depends on the local degree of nonlinearity. RS induces stochastic switching among dynamic modes with different levels of nonlinearity. The resulting mode-switching behavior makes the theoretical proof of mean-square stochastic stability mathematically challenging. To facilitate the analysis, researchers commonly model γ_k as a Bernoulli process and incorporate it into the Kalman gain and covariance update equations. The channel access state can also be modeled as a Markov chain, in which case the architecture is described as a Markov jump nonlinear system.

3.3. Deterministic Scheduling Strategies

Deterministic scheduling (DS) strategies allocate channel resources according to fixed or predefined rules, so that the transmission sequence can be predicted in advance. This mandatory transmission mechanism avoids the effects of channel contention. In the context of networked filtering, typical deterministic scheduling strategies include the round-robin (RR) protocol [88–90] and the try-once-discard (TOD) protocol [91].

RR scheduling is a static periodic strategy whose cyclic mechanism assigns channel access to each sensor in a fixed predefined order, such as $1 \rightarrow 2 \rightarrow \dots \rightarrow N$. Notably, this static allocation rule is independent of the current measurement content and the real-time system dynamics. As a time-driven deterministic strategy, RR offers several clear advantages, including ease of implementation, low network arbitration cost, and guaranteed long-term fairness. RR scheduling is usually modeled by:

$$S_k = \text{mod}(k, N) + 1, \quad (16)$$

where mod denotes the modulo operation. The result ranges from 0 to $N - 1$, and adding 1 maps it to 1 to N .

The TOD protocol is a typical data-based dynamic scheduling strategy. Unlike static protocols, dynamic schemes require all nodes to compute the measurement innovation in real time. Following a winner-take-all principle, the node with the largest innovation norm is granted channel access. Conversely, the unselected nodes are denied access, and their pending data packets are immediately discarded. The weighted try-once-discard (WTOD) protocol generalizes the maximum-error-first logic [92–94] by introducing sensor-specific weights λ_i to quantify the relative priority of each node. Accordingly, the algorithm selects the node S_k with the maximum weighted innovation for transmission. The selection criterion is mathematically formulated as:

$$\begin{aligned} S_k &= \arg \max_{i \in \{1, \dots, N\}} \lambda_i \cdot (\mathbf{y}_{i,k} - h_{i,k}(\hat{\mathbf{x}}_{i,k|k-1}))^T \\ &\quad \times (\mathbf{P}_{zz,k}^i)^{-1} (\mathbf{y}_{i,k} - h_{i,k}(\hat{\mathbf{x}}_{i,k|k-1})), \end{aligned} \quad (17)$$

where λ_i represents an external weighting factor. The weighting coefficient reflects the inherent importance of sensor i or the associated potential impact on estimation performance. Typically, the priority index is computed offline or updated dynamically. Notably, under the condition of uniform weighting where $\lambda_i = 1$ for all nodes

($i = 1, \dots, N$), the WTOD strategy degenerates to the standard TOD protocol.

Remark 4. For periodic DS protocols such as RR, the cyclic channel allocation rule gives rise to a periodically time-varying filtering system. Consequently, the error covariance converges not to a constant steady-state matrix, but to a periodic solution satisfying the condition $P_k = P_{k+T}$. This oscillatory convergence implies that the estimation accuracy fluctuates periodically. Estimation fidelity reaches its peak at certain time steps and deteriorates at others. To accommodate this periodic variation while preserving the recursive structure of the KF, a standard approach is to define a scheduling function $\sigma(k) \in \{1, 2, \dots, N\}$. This deterministic mapping explicitly specifies which sensor has access at the current time step, thereby allowing the filter to update P_k using only the information from the currently scheduled sensor.

3.4. Collaboration and Optimization-Driven Scheduling Strategy

In recent years, collaborative-optimization-based scheduling (COS) strategies have emerged as an important research direction in networked filtering. Unlike random and deterministic scheduling strategies, collaborative-optimization-based approaches formulate communication decisions as mathematical optimization problems [95–97]. To a certain extent, this paradigm overcomes the limitations of traditional time-triggered and event-triggered methods. Specifically, the scheduling decision is treated as an optimization variable, whereas performance metrics such as the estimation error covariance or uncertainty are defined as cost functions to be minimized [98].

Optimization theory provides an effective framework for balancing communication resource consumption and estimation performance. By introducing Lagrange multipliers for communication constraints, constrained estimation problems can be transformed into Lagrangian formulations, and optimal communication strategies can be derived through Karush–Kuhn–Tucker (KKT) conditions [99]. The joint optimization of distributed transceiver parameters and estimation performance under power constraints has been addressed using a KKT condition-based approach [100], while optimal precoding solutions for decentralized estimation have been derived through Lagrangian optimization within the minimum variance distortionless precoding framework [101]. These studies provide useful insights into resource-aware joint optimization in communication-constrained estimation systems.

Although Lagrange multiplier and KKT-based approaches provide analytical solutions for structured optimization problems with explicit models and constraints, their applicability may be limited in highly dynamic or model-uncertain environments due to the non-convexity and time-varying nature of scheduling decisions. Therefore, collaborative optimization frameworks have further incorporated different decision-making strategies according to the available system information. Static offline optimization can be adopted when system dynamics and communication conditions are known a priori, whereas dynamic online planning, such as model predictive optimization, can adapt scheduling decisions according to real-time system evolution. Moreover, reinforcement learning approaches have been explored for complex or unknown environments where accurate mathematical models are difficult to obtain, enabling data-driven resource allocation and scheduling [102–104].

Remark 5. Under collaborative-optimization-based scheduling, temporal coupling and future-performance prediction can turn a one-step optimization problem into a complex dynamic programming problem, while the dependence of estimation quality on communication decisions precludes the offline computation of an optimal cooperative strategy. Specifically, since the estimation error term is typically nonconvex with respect to the decision variable, determining the globally optimal strategy requires computationally intensive global search algorithms. Consequently, practical algorithm design prioritizes the identification of suboptimal yet stable solutions over the pursuit of the exact global optimum.

3.5. Encoding and Decoding Strategy

To ensure data reliability and improve communication efficiency, it is crucial to design coordinated encoding-decoding mechanisms (EDM). Motivated by the need to conserve communication resources, filtering problems involving encoding-decoding schemes have attracted increasing attention [105–107]. Specifically, these coding architectures exploit prior knowledge of the system model to perform strategic information compression at the transmitter, followed by reconstruction at the receiver through model synchronization. This model-assisted approach ensures that the limited communication bandwidth is used to transmit the most informative data, thereby improving estimation accuracy. The encoder is typically modeled as:

$$l_i(k) = \mathcal{F}(\mathbf{y}_{i,k}), \quad (18)$$

and the corresponding decoder is

$$\tilde{\mathbf{y}}_{i,k} = \mathcal{G}(l_i(k)), \quad (19)$$

where $\tilde{\mathbf{y}}_{i,k}$ is the decoded value of $\mathbf{y}_{i,k}$ at time k and $l_i(k)$ is the codeword to be transmitted. $\mathcal{F}(\cdot)$ denotes the encoding function, and $\mathcal{G}(\cdot)$ denotes the decoding function.

It is worth noting that, when the measured data exhibit strong temporal correlation, difference encoding with respect to a previous observation or predicted measurement can be more efficient than directly encoding the full raw measurement. A typical prediction-residual form is given by $\mathbf{r}_{i,k} = \mathbf{y}_{i,k} - \hat{\mathbf{y}}_{i,k|k-1}$. This difference is also referred to as the innovation or increment. If the system state changes slowly, the dynamic range of $\mathbf{r}_{i,k}$ is much smaller than that of the absolute measurement $\mathbf{y}_{i,k}$. As a result, fewer bits are required for encoding, thereby improving coding efficiency.

Remark 6. In the nonlinear filtering framework, the main challenge in filter design arises from the stepwise nature of the encoding and decoding functions and the limited coding range. For componentwise uniform quantization with a common step size Δ and no saturation, the encoding and decoding error $\mathbf{e}_{i,k} = \mathbf{y}_{i,k} - \tilde{\mathbf{y}}_{i,k}$ satisfies $\|\mathbf{e}_{i,k}\|_\infty \leq \Delta/2$. When a uniform-error approximation is adopted, each component of $\mathbf{e}_{i,k}$ is modeled as uniformly distributed over $[-\Delta/2, \Delta/2]$. This encoding and decoding error is then incorporated into the estimation covariance of the Kalman filter, and the filter gain is obtained by minimizing the upper bound of the estimation covariance.

3.6. Hybrid Communication Mechanisms

In practical networked systems, communication constraints usually arise from multiple aspects, including limited bandwidth, energy consumption, channel congestion, and unreliable transmission. Consequently, a single communication management strategy may not achieve a desirable trade-off between estimation accuracy and communication cost. Recently, hybrid communication mechanisms (HCM) that jointly integrate triggering, scheduling, and encoding strategies have attracted increasing attention in NCSs [108, 109]. Such joint designs are particularly beneficial in multi-agent networks, where multiple agents need to collaboratively exchange information under constrained and unreliable communication environments. For example, resilient distributed estimation and control of multi-agent systems have demonstrated that event-triggered and quantized communication strategies can effectively reduce transmission requirements while maintaining reliable information exchange under communication uncertainties and disturbances [73, 108, 110].

Assume that a binary variable $\gamma_k \in \{0, 1\}$ is introduced to indicate whether information is transmitted at time k , $\sigma(k) \in \{1, 2, \dots, N\}$ denotes the index of the sensor selected for transmission, and b_k represents the transmission bit rate. Then, different communication resource management strategies can be uniformly characterized by the communication decision variable

$$\mathcal{C}_k = (\gamma_k, \sigma(k), b_k), \quad (20)$$

Under this communication mechanism, the filtering recursion can be generally formulated as

$$\hat{\mathbf{x}}_{k|k} = \mathcal{T}(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{y}_k, \mathcal{C}_k), \quad (21)$$

where $\mathcal{T}(\cdot)$ denotes the filtering update operator constrained by the communication decision.

Remark 7. HCM mainly provide two benefits. First, joint design enables the simultaneous optimization of communication frequency, sensor selection, and transmitted information amount, thereby achieving efficient resource allocation. Second, hybrid strategies directly influence filtering performance and stability by regulating the availability, accuracy, and timeliness of measurement information. However, hybrid communication mechanisms also suffer from strong coupling among triggering variables, scheduling decisions, and encoding parameters, which significantly increases the difficulty of theoretical analysis. Therefore, establishing a unified communication decision model that incorporates triggering probabilities, scheduling strategies, and quantization parameters into a joint optimization framework has become an important research direction for nonlinear filtering under hybrid communication constraints.

Table 2 presents a systematic comparison of representative communication-efficient strategies, including event-triggered, scheduling, optimization-based, and encoding-based methods. The comparison focuses on estimation accuracy, convergence behavior, computational complexity, and communication reduction, highlighting the fundamental trade-off between estimation performance and resource consumption. In existing studies, communication reduction is commonly quantified by the transmission rate, defined as the ratio between the number of successful transmissions and the total decision instants, i.e., $\rho_i = M_i^{\text{tr}}/M$, where M_i^{tr} denotes the number of transmissions of node i , and M represents the

total decision instants. A smaller transmission rate indicates reduced communication burden. For encoding-based approaches, communication cost is typically measured by the transmitted bit rate or allocated bits. These metrics provide quantitative criteria for evaluating communication-efficient strategies [55,99,105].

Table 2. Comparison of representative communication-efficient strategies.

Category	Strategy	Steady-State Estimation Error Bounds	Convergence Speed	Complexity	Communication Reduction Measure
ETS	SETS	Bounded error under a properly selected fixed threshold	Moderate	Low	Transmission rate ρ_i
	DETS	Improved error bound through adaptive triggering	Faster adaptation to system variations	Medium	Adaptive transmission rate ρ_i
	RETS	Expected bounded covariance under suitable triggering probability	Probability-dependent convergence	Medium	Average transmission probability $\mathbb{E}(\gamma_{i,k})$
DS	RR	Bounded estimation error under periodic access	Predictable convergence behavior	Very low	Fixed transmission rate ρ_i
	TOD	Reduced estimation error bound under priority-based access	Faster information acquisition than RR in many cases	Medium	Improved estimation efficiency under fixed communication rate
RS	Bernoulli	Mean-square bounded error under suitable access probability	Stochastic convergence	Low	Probabilistic transmission rate $\rho_i = p_i$
	Markov	Mode-dependent boundedness	Transition-dependent convergence	Medium	Mode-dependent transmission probability
COS	Offline	Near-optimal estimation performance under optimization constraints	Stable online execution after offline design	High	Optimized transmission strategy
	Online	Adaptive estimation performance under real-time optimization	Online adaptation	High	Adaptive communication allocation
	RL	Policy-dependent estimation performance	Performance improves with training	Very high	Learned transmission policy
EDM	Quantization	Error bounded by quantization resolution	Accuracy-dependent	Low-medium	Bit rate b_k
	Differential	Error bounded under coding constraints	Prediction-dependent	Medium	Reduced bit rate via innovation coding
HCM	ETS + Scheduling + EDM	Bounded error under coupled communication constraints	Adaptive	Medium-high	Joint optimization of ρ_i and b_k

4. Nonlinear Distributed Filtering under Communication Scheduling

The scalability and stability of distributed architectures have driven the rapid development of distributed filtering techniques. Although early studies primarily focused on linear systems, practical engineering applications typically involve nonlinear dynamics. Consequently, distributed filtering for nonlinear systems has become a highly important and active research area. This section reviews recent advances in nonlinear distributed KF, with particular emphasis on the associated challenges under resource-constrained conditions.

4.1. Nonlinear Kalman Filter under Event-Triggered Schemes

Because of their simple design and ease of analysis, SETSs have played an important role in early studies on distributed nonlinear KF. In most cases, the innovation sequence has been used to define the triggering condition in SETSs [70–72], and such schemes have been further extended in recent years. For example, in [111], the triggering condition has been designed as a static threshold based on the magnitude of measurement variation, and a scalable distributed filter for discrete-time nonlinear systems has been proposed. Theoretical analysis has shown that the filtering error has remained bounded in the mean-square sense. Similarly, in [112], the event-triggering condition has been designed based on the innovation term, resulting in a residual-based event-triggered CKF whose stochastic stability has been analyzed. In [113], a static-trigger-based non-Gaussian filter has been proposed, which has addressed the limitations of traditional static-trigger Kalman filters in handling non-Gaussian noise. In addition, in [114], the triggering mechanism has been integrated with robust filtering by modeling the non-triggered case as a non-Gaussian process, where the Kalman gain has been designed according to the maximum correntropy criterion.

Compared with SETSs, DETSs have offered greater flexibility and adaptability. Under DETSs, the core issue in filter design lies in how to develop an effective triggering function and a time-varying threshold that achieve an appropriate balance between communication rate and estimation accuracy [73]. In recent years, filter design based on dynamic triggering has become a research focus. For instance, in [74], the triggering condition has been

constructed using both the information matrix and the state estimate, and system stability has been analyzed under specific assumptions. Similarly, in [115], a distributed diffusion Kalman filter for nonlinear systems has been investigated, where data have been transmitted only when preset conditions have been satisfied, and stability has been verified through stochastic stability theory. In [116], a dynamic mechanism over a finite time horizon has been designed, and the stability of the unified framework has been proved via Lyapunov theory. Additionally, in [117], a resilient extended Kalman filter with consensus estimation capabilities has been developed, which has conserved computational resources and bandwidth while maintaining the desired performance.

Unlike deterministic event-triggered mechanisms, stochastic event-triggered schemes have introduced probabilistic triggering rules or auxiliary random variables into transmission decisions. Consequently, even under the same measurement or innovation information, whether a transmission is triggered may remain random, leading to non-deterministic and generally aperiodic transmission instants. In [75], a stochastic event-triggered mechanism based on probabilistic transmission rules has been developed, where a Bayesian inference approach is employed to recover hidden triggering information over Gaussian channels. The proposed method achieves bounded estimation errors without requiring explicit triggering decisions. In [118], a stochastic event-triggered CKF has been proposed for power system dynamic state estimation, effectively reducing communication transmissions while maintaining estimation accuracy. In [76], a stochastic event-triggered robust UKF has been developed for USV parameter estimation, where the probabilistic triggering scheme and robust filtering framework improve communication efficiency and estimation performance under uncertainties. In [119], a mixed event-triggered distributed UKF has been proposed for nonlinear systems by combining measurement-based and innovation-based triggering rules, achieving a trade-off between communication reduction and estimation accuracy.

4.2. Nonlinear Kalman Filter under Random Scheduling Strategies

Under RS mechanisms, the key challenge for distributed nonlinear Kalman filtering has been to maintain stability in the presence of stochastic data transmission. In algorithms such as the Distributed Extended Kalman Filter and Distributed Unscented Kalman Filter, random data arrivals have caused fluctuations in the information matrices and vectors during fusion, making convergence difficult to ensure. To suppress the resulting estimation fluctuations, the scheduling indicator $\gamma_{i,k}$ has been directly incorporated into the filtering recursion in existing studies. In [87], neighbor selection has been modeled as a stochastic process for consensus filter design. In [83], a random access protocol has been employed to manage communication between sensors and filters, thereby optimizing transmission sequences while mitigating data collisions. In [120], cubature Kalman fusion filtering for nonlinear systems under the combined effects of the stochastic communication protocol, dynamic bias, and channel noise has been investigated, with local filters designed and information fused using an inverse-covariance-intersection fusion rule. In [121], the stochastic communication protocol has been employed to randomly schedule information transmission among neighboring nodes so as to reduce communication conflicts, and a recursive filter has been designed by minimizing the derived upper bound, with sufficient conditions established based on Riccati-type difference equations.

Under the RS strategy, stochastic stability theory has been used to analyze the properties of systems with random error dynamics. This probabilistic framework has been crucial for proving that the state estimation error remains bounded in the mean-square sense or asymptotically converges to zero. Notably, at the algorithm design level, information-weighted consensus mechanisms have often been adopted in fusion strategies to enhance performance. Specifically, when data from a node are unavailable (i.e., $\gamma_{i,k} = 0$), a compensation mechanism must be activated. In such cases, the most recent valid observation or model-based prediction has typically been used by fusion centers or neighboring nodes to compensate for the missing data.

4.3. Nonlinear Kalman Filter under Deterministic Scheduling Strategies

Unlike RS strategies, deterministic scheduling strategies explicitly specify which node accesses the shared channel at each time step. Owing to the prescriptive nature of the allocation, such structured protocols have facilitated the performance analysis and stability verification of distributed nonlinear Kalman filters. In [122], a filter quantifying the impact of scheduling has been designed, specifically addressing the coexistence of stochastic nonlinearities and deterministic constraints. In [123], a resilient mechanism has been proposed to handle periodic data loss caused by the RR protocol; the compensatory technique has taken both sensor saturation and channel noise into consideration, and it has been proven that the mean-square error remains bounded. In [94], attention has been focused on the numerical fluctuations of the filter gain, ensuring that the CKF converges even under the combined effect of protocol-induced intermittent behavior and gain perturbations. In [124], a novel augmentation framework has been proposed for the cyclic RR protocol, where periodic intermittency is not treated as simple packet dropouts;

instead, the associated uncertainties are modeled as additional state variables for augmented estimation.

For deterministic scheduling, the primary research focus has been placed on the design of optimal weight functions or priority rules. By developing a deeper understanding of the error propagation mechanism in nonlinear filtering, the optimization objective of minimizing mean-square error bounds has been achieved [94, 125]. In addition, conventional deterministic schemes have been difficult to apply directly to wide-area networks (WAN) because WAN traffic is characterized by statistical multiplexing and non-periodic deadline constraints. To address this issue, deadline-aware routing and scheduling mechanisms can be employed to provide deterministic transmission guarantees while accommodating such traffic characteristics [126]. Under an extended RR multichannel protocol, energy-constrained stealthy attacks can be jointly optimized in terms of attack matrices and attack scheduling to maximize their impact on remote state estimation performance [127].

4.4. Nonlinear Kalman Filter under Collaboration and Optimization-Driven Scheduling Strategy

To improve estimation performance in resource-constrained environments, co-optimized scheduling strategies have emerged as an important research direction. The underlying principle has been to determine the optimal scheduling scheme for each communication time slot by solving optimization problems [128, 129]. Information-aware scheduling policies have been developed to enhance system awareness by reducing conditional uncertainty or maximizing mutual-information-based utility under communication constraints [130, 131]. Under communication intermittency induced by energy harvesting, estimation performance has commonly been optimized by minimizing an error-covariance-based criterion [132–134].

A primary challenge in co-optimization has been the formulation of an appropriate objective function, which has typically been aligned with KF estimation performance. For example, in [135], observer design has been formulated as a regularized optimization problem to balance estimation error and communication cost, and a multiblock alternating direction method of multipliers algorithm with an LMI-based warm start has been proposed to solve this problem. In [136], a multi-channel sensor scheduling scheme integrated with a quantization mechanism has been proposed, and the desired filter gain has been obtained by minimizing the upper bound of the error covariance. In [137], a periodic path-planning method for mobile sensors has been proposed by integrating a dynamic mode decomposition reduced-order model with a time-forward greedy search mechanism, with the objective of minimizing the condition number of the trajectory-dependent observability matrix. To address the computational burden of model-based scheduling, reinforcement-learning-based approaches have increasingly been adopted in recent studies, through which sensor or communication scheduling policies can be learned for dynamical monitoring, target tracking, and remote state estimation under resource limitations and varying channel conditions [104, 138–141].

Another important challenge has been the computational complexity of optimization. For the related integer programming formulations, obtaining an exact solution has usually required solving nonconvex or combinatorial optimization problems, which has often led to a high computational burden [142]. More specifically, the prediction and update steps in nonlinear KF have already involved complex nonlinear functions and computation-intensive matrix operations. As a result, incorporating nonlinear coupled dynamics into the optimization objective while maintaining computational feasibility has been extremely difficult. Accordingly, attention has been directed toward the development of low-complexity suboptimal or approximate algorithms.

4.5. Nonlinear Kalman Filter under Encoding-Decoding Strategy

In NCSs, effective encoding strategies have been regarded as one of the key approaches to saving communication resources [105]. The main objective has been to preserve useful information through encoding and decoding under bandwidth and energy constraints, thereby minimizing the loss of estimation performance.

The encoding-decoding process is essentially a nonlinear mapping, and its inherent discontinuity has greatly increased the complexity of the error dynamics between the original nonlinear system and its digital representation. In other words, in nonlinear Kalman filter design, the encoding-decoding error cannot be simply modeled as Gaussian white noise. To address such non-Gaussian distortion, the co-design of encoding-decoding strategies and fusion algorithms has been required for distributed information fusion. This integrated co-design methodology has ensured that consensus estimates derived from quantized data converge to a neighborhood of the globally optimal estimate. In [143], a local distributed filter has been constructed for time-varying multi-rate nonlinear systems, and the filtering gain has been obtained by minimizing the trace of the upper bound of the error covariance. In [24], a recursive filtering algorithm has been developed for networked time-varying systems with random measurement outliers, where probabilistic encoding-decoding has been adopted for digital transmission and active detection has been used to exclude contaminated measurements from filtering. In [107], an improved encoding-decoding mechanism for measurement outputs has been developed based on uniform quantization, under which the decoding error has been

guaranteed to remain stochastically bounded subject to a specified bit-rate constraint.

For nonlinear filters subject to bit-rate-constrained encoding schemes, the primary objective of performance analysis has been to show that the state estimation error remains bounded in the mean-square sense under bit-rate constraints. A prevailing approach has been to incorporate the statistical properties of quantization errors into Lyapunov stability analysis. Through such stability assessment, the theoretical relationship between the minimum required bit rate and the upper bound of the estimation error covariance has been established [144,145].

4.6. Nonlinear Kalman Filter under Hybrid Communication Strategy

Compared with individual communication management strategies, HCM can exploit the complementary advantages of different resource allocation schemes, providing more flexible solutions for balancing communication efficiency and estimation performance. For example, ref. [146] has demonstrated that, within an event-triggered estimation framework, a properly designed measurement compression strategy can reduce redundant information while preserving essential measurements, thereby decreasing estimation uncertainty and improving estimation accuracy. This result indicates that the coordinated optimization of multiple communication mechanisms can further reduce communication overhead while maintaining filtering performance.

Although such joint design introduces additional complexity in model analysis and parameter optimization, it remains an important research direction for resource-constrained nonlinear estimation. In [147], the nonlinear distributed filtering problem under the joint effects of event-triggered mechanisms and finite-bit quantization has been investigated, where the triggering threshold and quantization strategy are jointly designed to reduce bandwidth requirements. In [148], a quantized innovation-based event-triggered nonlinear state estimation method has been proposed, where the event-triggered mechanism reduces communication frequency and the quantization scheme alleviates instantaneous bandwidth limitations. Furthermore, in [149], a dynamic event-triggered mechanism has been integrated with an encoding-decoding strategy, where the triggering rule and information compression scheme are jointly optimized to reduce communication burden while guaranteeing exponential stability of the estimation error.

Under HCM, multiple resource management strategies jointly affect the information transmission and acquisition processes, making the stability analysis of nonlinear filtering more challenging. Existing studies usually establish a unified communication model incorporating factors such as event-triggering variables, scheduling strategies, and quantization levels. Then, stochastic Riccati equations or Lyapunov methods are employed to characterize the impact of communication constraints on estimation error propagation. By analyzing the boundedness of error covariance, mean-square convergence, and stochastic stability conditions, sufficient criteria for preserving filtering performance can be derived.

5. Conclusions and Challenging Issues

In this paper, a comprehensive overview of recent advances in nonlinear KF for NCSs has been provided from the perspective of resource constraints. First, the practical background of networked nonlinear Kalman filtering has been briefly introduced, with particular emphasis on communication challenges. Several mainstream nonlinear Kalman filters have then been reviewed, together with typical communication resource constraints. Subsequently, common communication scheduling strategies employed in modern engineering applications have been outlined. Following this, advances in nonlinear KF under scheduling strategies have been surveyed. The classification methods, filtering schemes, and main objectives summarized in this paper are intended to assist practitioners in identifying suitable solutions for state estimation problems under specific system configurations and resource constraints. It is worth noting that, although numerous theoretical and methodological insights have been proposed in recent years for the design and performance analysis of networked nonlinear Kalman filters, the establishment of general principles has remained challenging because of the complexity and diversity of target systems, network environments, and task objectives. Finally, several promising yet challenging directions and issues have been highlighted for future research.

(1) A Unified Theoretical Framework for Complex Network Dynamics: Existing studies have often considered only one limiting factor at a time, such as nonlinear dynamics, network-induced delays, packet loss, quantization errors, or scheduling protocols. In practical engineering applications, however, these factors are strongly coupled and often occur simultaneously. For example, event-triggered communication changes the statistical properties of measurement arrivals, which directly affects the design of the filter gain. Likewise, highly nonlinear systems are generally more sensitive to data loss. Therefore, jointly addressing the coupled effects of nonlinear dynamics, complex network phenomena, and resource constraints remains an important direction for improving achievable performance and establishing general design principles.

(2) Adaptive and Learning-Based Filtering Mechanisms: Traditional nonlinear Kalman filters have largely relied on accurate system models and noise statistics. In practical NCSs, however, system parameters often vary over

time, and noise statistics are usually unknown or non-Gaussian. As a result, filters with fixed parameters struggle to maintain an effective balance between resource consumption and estimation accuracy during long-term operation. The core challenge in the online joint estimation of system states and unknown or time-varying model parameters has been to effectively handle the non-Gaussian and correlated equivalent noise induced by network dynamics.

(3) Robust and Secure Filtering in Vulnerable Environments: The deployment of open communication networks exposes filtering processes to cyber-security threats. For nonlinear systems, such attacks can significantly degrade estimation performance or even destabilize filtering due to complex uncertainty propagation. It should be noted that attack modeling in networked filtering research primarily serves as a vulnerability assessment tool rather than developing attack strategies. By identifying weaknesses under adverse conditions, these studies facilitate the design of resilient filtering algorithms and effective defense mechanisms. Therefore, distinguishing nonlinear modeling errors from malicious data perturbations while ensuring estimation accuracy remains a critical challenge. Future research may integrate fault diagnosis and anomaly detection with secure state estimation to jointly realize attack detection, isolation, and resilient filtering, thereby enabling a transition from passive robustness to active defense against cyber-attacks.

(4) Graph Learning and Dynamic Topology Inference: Existing studies have usually assumed that the communication topology is known a priori or remains fixed. Under strict resource constraints, however, the network topology itself should be treated as a dynamic optimization variable. In dynamic topology settings, one key challenge has been to enable the system to automatically identify and prune communication links with low information gain while retaining only the sparse edges that are most critical for nonlinear state recovery. In addition, in resource-constrained networks, the algorithm should be able to adaptively reconfigure the topology when nodes fail because of energy depletion, while preserving distributed consensus and observability.

Author Contributions

K.L. conducted the literature review, prepared the visualizations, and wrote the original draft. Y.W. contributed to the conceptualization and organization of the review and revised the manuscript. F.W. supervised the work and reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper

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