

# A Comprehensive Review on Relay-Assisted State Estimation in Networked Systems: Architectures, Algorithms, and Challenges

Ziye Wang, Zidong Wang, Qinyuan Liu, Shuang-Hua Yang, and Xiao He

**Abstract**—Relay-assisted transmission has emerged as an effective means to enhance communication reliability and extend transmission range in networked systems. Integrating relay mechanisms into state estimation architectures can significantly enhance both accuracy and stability in remote and resource-constrained environments. This paper provides a comprehensive review of relay-assisted state estimation (RASE) for networked systems. First, the fundamental architectures of relay-assisted networks are formalized, and commonly used relay protocols are introduced including their mathematical models, engineering insights and multi-dimensional comparison. Then, the influence of relays on system performance is analyzed and mainstream filtering algorithms in the relay-assisted context are compared, followed by a general workflow of RASE. Subsequently, state estimation algorithms developed for relay-assisted systems are systematically surveyed, covering nonlinear systems, complex dynamical networks, and several representative special system classes. Furthermore, the paper reviews RASE methods addressing key network-induced phenomena. They typically include fading channels, communication delays, and packet losses. Issues related to energy management and security are also discussed, such as energy harvesting, power scheduling, eavesdropping, and denial-of-service attacks. Finally, the paper summarizes current research progress and highlights several open problems and promising directions for future investigation. The review aims to provide a structured reference and insights for researchers working on relay-assisted estimation in large-scale cyber-physical systems.

**Index Terms**—Relay-assisted state estimation, networked systems, distributed filtering, network-induced phenomena, nonlinear systems, energy-aware estimation, secure estimation, multi-hop communication.

This work was supported in part by the European Union’s Horizon 2020 Research and Innovation Programme under Grant 820776 (INTEGRADDE), the Engineering and Physical Sciences Research Council (EPSRC) of the UK, the Royal Society of the UK, and the Alexander von Humboldt Foundation of Germany.

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## I. INTRODUCTION

The state of an object typically refers to a set of physical quantities that describe its dynamic behavior [6], such as position, velocity, acceleration, and angle. State estimation has a long history, dating back thousands of years to early navigation problems in which the positions of ships at sea needed to be inferred. Its theoretical foundations trace to probability theory developed by Pascal and Fermat, as well as Bayes’ rule. In the nineteenth century, Gauss introduced the method of least squares to recover the orbit of Ceres from noisy observations and established the optimality of least-squares estimators under Gaussian noises. In the mid-twentieth century, Kalman’s seminal work [37] provided a systematic framework for linear Gaussian state estimation, widely known as the Kalman filter (KF), which is statistically optimal in the minimum mean-square error (MMSE) sense for linear Gaussian systems. For nonlinear systems, the extended Kalman filter (EKF, based on first-order linearization), the unscented Kalman filter (UKF, based on the unscented transform), and the cubature Kalman filter (CKF, using spherical-radial cubature rules) serve as effective extensions for nonlinear systems with Gaussian noise. Although no longer optimal, these methods remain computationally efficient and suitable for real-time estimation. Beyond Gaussian assumptions, particle filters (PFs) and Gaussian mixture filters extend state estimation to general nonlinear and non-Gaussian settings.

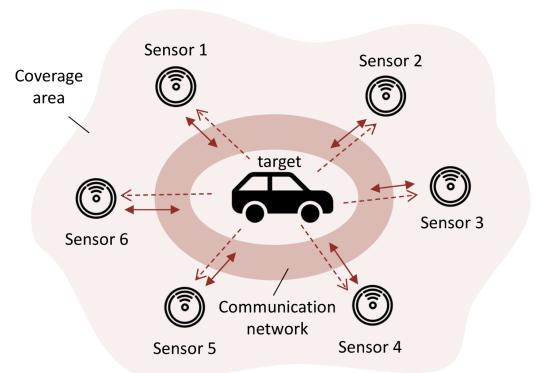


Fig. 1: The structure framework of traditional distributed state estimation in multi-sensor networked systems.

Recently, the rapid expansion of networked systems such as smart grids and the industrial Internet of things has significantly increased the number of intelligent devices, while ap-

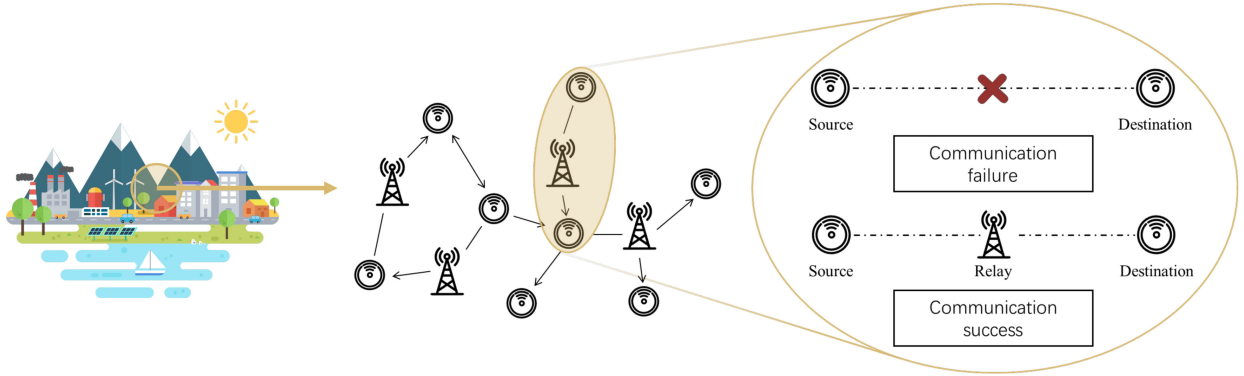


Fig. 2: The topology for relay-assisted distributed state estimation.

application scenarios including intelligent transportation and environmental monitoring impose increasingly stringent requirements on latency, energy consumption, security, and estimation accuracy. Moreover, many practical applications require large-scale sensing, which places substantial pressure on communication networks and resource management. As a result, real-time, robust, and high-precision remote state estimation has become a core technology of broad interest. However, the energy available to each sensor is limited, which constrains the power allocated for signal transmission. Consequently, sensors cannot transmit signals over arbitrarily long distances [58]. In addition, signal quality is degraded by adverse physical phenomena such as multipath propagation and shadowing from obstacles [59]. To mitigate signal degradation during long-distance transmission, relay-based communication techniques have been widely adopted between source and destination nodes [125], [4]. Such techniques strengthen link reliability, extend communication range, reduce total energy expenditure, and maintain network connectivity while preserving estimator performance [55], [15].

To illustrate the structural and functional differences introduced by relay integration, the traditional relay-free framework is compared with a relay-enhanced architecture. The traditional distributed framework of a multi-sensor networked system without relay assistance is illustrated in Fig. 1. Sensors deployed within the monitoring area collectively acquire and process information about the target object and exchange information through a shared communication network to accomplish state estimation. In contrast, the topology incorporating relays into distributed state estimation is depicted in Fig. 2. It consists of source nodes, relay nodes, and remote destination nodes (the neighbors of source nodes), where arrowed lines indicate the direction of data transmission. The introduction of relays adds connections to the network topology, extends effective observation coverage, and mitigates interference during signal transmission. Furthermore, the utilization of remote destination nodes is enhanced, leading to improved overall performance of distributed state estimation.

While numerous review articles have been available on the fundamental principles, technological developments, and applications of networked state estimation [93], [87], [21], [46], relay-assisted state estimation (RASE) in networked systems has not been comprehensively reviewed. An overview

of typical works on RASE reviewed in this paper is presented in Fig. 3. The remainder of this paper is organized as follows. Section II introduces commonly used relay types and their working mechanisms in RASE. Section III analyzes the impact of relays on the overall system performance, compares mainstream filtering algorithms within the relay-assisted framework and outlines general execution workflow of RASE. Section IV summarizes estimation algorithms for different relay-assisted networked systems. Section V reviews network-induced phenomena and the corresponding RASE algorithms. Sections VI and VII discuss energy management and security issues, respectively. Finally, Section VIII provides concluding remarks and future research directions. Representative works on RASE are summarized in Fig. 3 for the convenience of readers.

## II. COMMONLY USED RELAY CATEGORIES

Relay-assisted technologies have evolved significantly from early relaying concepts [82], [98] and the classical relay channel model [15] to a diverse family of relay types. In this section, commonly used relay categories are classified, and their operational principles are explained together with representative mathematical formulations.

### A. Amplify-and-forward Relay (AF)

The AF relay is a fundamental technology in modern wireless communication systems [7], [33], [100]. It is employed to enhance system performance by receiving, amplifying, and retransmitting signals, thereby extending reliable communication range and improving transmission robustness. Its primary function is to mitigate signal degradation caused by path loss and fading during long-distance transmission between source sensors and destination nodes.

In [49], AF relays have been incorporated into the sensor-to-filter communication link, forming a two-stage transmission architecture. In this framework, the AF relay first receives the measurement signal  $y_{i,s}$  from the source sensor. This reception process is affected by the stochastic channel gain  $\gamma_{i,s}$  and corrupted by additive channel noise  $m_{i,s}$  in the sensor-relay channel, as described by

$$z_{i,s} = \sqrt{E_i^l} \gamma_{i,s} y_{i,s} + m_{i,s}$$

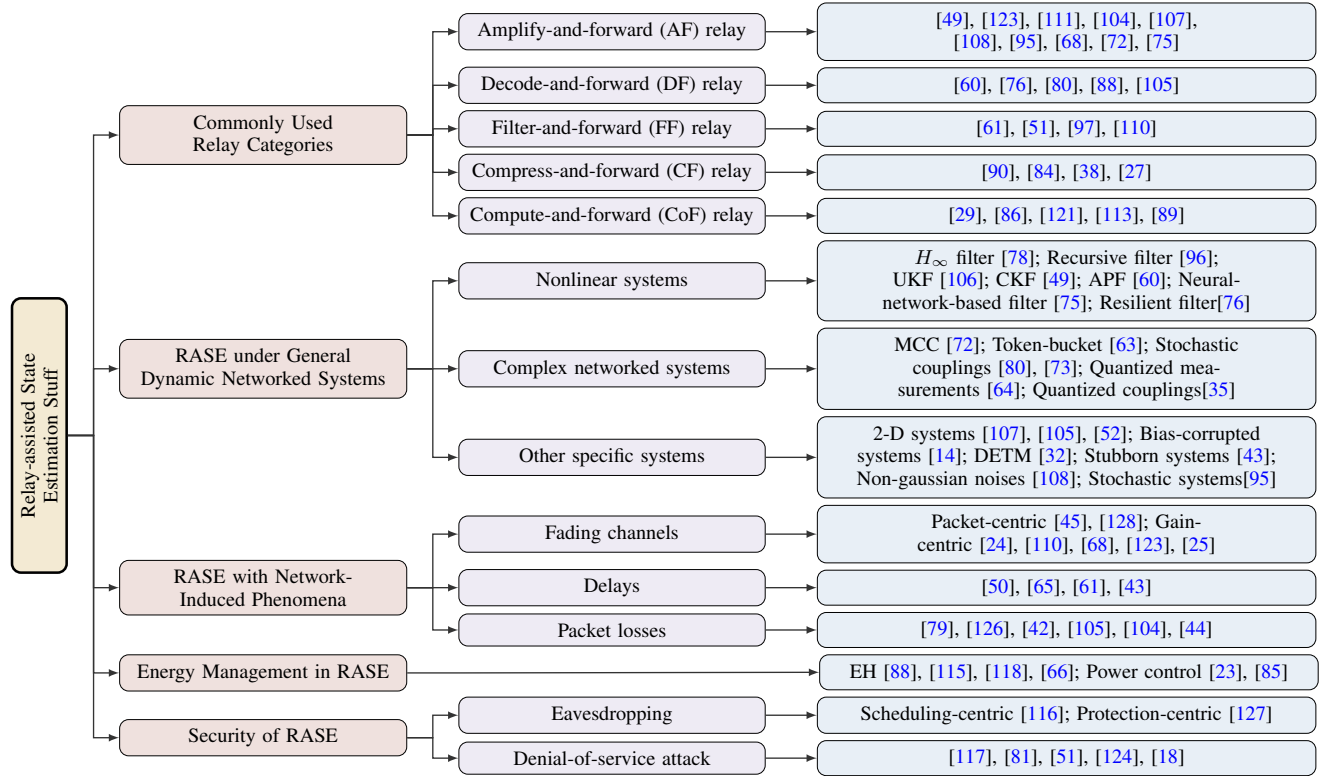


Fig. 3: An overview of typical works on RASE.

Here,  $E_i^l$  denotes the average signal energy allocated by the sensor for transmitting signal  $y_{i,s}$ . A larger  $E_i^l$  corresponds to stronger interference suppression capability and improved signal robustness. Nevertheless, the energy budget of the sensor is strictly constrained and cannot be increased arbitrarily. Moreover, due to multipath propagation and environmental interference, the channel parameter  $\gamma_{i,s}$  is commonly modeled as a random variable with bounded probabilistic uncertainties to better capture practical wireless conditions.

It is clear that the relay amplifies the received signal  $z_{i,s}$  and forwards it to the filter. This retransmission process is also affected by the stochastic channel gain  $\xi_{i,s}$  and additive noise  $n_{i,s}$  in the relay-filter channel, leading to

$$\vec{y}_{i,s} = \alpha_{i,s} \sqrt{E_i^r} \xi_{i,s} z_{i,s} + n_{i,s}$$

where  $\alpha_{i,s}$  is the amplification factor,  $E_i^r$  represents the average signal energy allocated by the relay, and  $\vec{y}_{i,s}$  denotes the signal finally received by the filter.

AF relays exhibit low computational complexity and straightforward implementation, as only linear amplification is applied to the received signals without decoding. Consequently, research on AF relays has been relatively mature, including studies on variable-gain relays [14], [56] and fixed-gain relays [54], [67], and applications such as over-the-air computation have been reported [101], [13], [102]. However, although AF relays effectively alleviate long-distance transmission limitations and reduce hardware costs, they introduce additional challenges for state estimation due to stochastic channel variations, probabilistic uncertainties, and cumulative noise amplification.

### B. Decode-and-forward Relay (DF)

The DF relay establishes reliable communication links between source sensors and remote destination nodes by adopting a decode-then-retransmit strategy [2], [122], [120]. In addition to compensating for signal attenuation over long distances, the decoding process enables the integration of error correction mechanisms, which leads to improved reliability and system performance. As a result, DF relays are widely adopted in various application scenarios [34], [91], [17].

For example, in [105], the source sensor measurement  $y_k$  is first encoded according to a predefined rule, generating an encoded signal  $\theta_k$  for transmission to the DF relay:

$$\theta_k = \mathcal{E}(y_k)$$

where  $\mathcal{E}$  denotes a vector-valued encryption function. Upon receiving  $\theta_k$ , the DF relay performs decoding through the operation  $\mathcal{D}$  to recover the signal:

$$\vec{y}_k = \mathcal{D}(\theta_k)$$

and the decoded signal  $\vec{y}_k$  is then forwarded to the filter via the relay-filter channel.

In contrast to AF relays, DF relays eliminate noise accumulation in the sensor-relay link by decoding the received signals. However, this advantage is accompanied by increased computational complexity and potential decoding errors, which must be carefully accounted for in estimator design.

### C. Filter-and-forward Relay (FF)

The FF relay enhances communication reliability and estimation accuracy by performing real-time filtering on received

signals prior to retransmission [97], [39], [1]. This mechanism is widely employed due to its favorable trade-off between computational complexity and estimation performance [40], [94].

In [61], FF relays have been deployed between sensors and remote fusion estimators and integrated into a distributed fusion architecture. Each FF relay utilizes the received measurement  $\hat{y}_{i,k+1}$  to compute a local state estimate  $\bar{x}_{i,k+1|k+1}$  through a filtering operation:

$$\bar{x}_{i,k+1|k+1} = \mathcal{F}(\hat{y}_{i,k+1}, \bar{x}_{i,k|k})$$

where  $\mathcal{F}$  denotes the specific filtering function. The resulting state estimates are subsequently transmitted to the remote fusion estimator for further fusion.

Unlike AF and DF relays, FF relays actively generate state estimates and suppress channel-induced disturbances through filter gain design. This capability significantly improves the robustness of state estimation in complex network environments.

#### D. Compress-and-forward Relay (CF)

In CF relaying, the received signal is first processed by a compression or quantization function and then transmitted to the destination node [90], [84], [38]. The CF relay broadcasts a compressed version of the received signal, while exploiting correlation with previously transmitted information that is known at the receivers.

For instance, in [27], remote radio heads (RRHs) in a cloud radio-access network architecture act as CF relays. The signal  $y^{ul}$  transmitted from users to the  $l$ th RRH is compressed as

$$\tilde{y}^{ul} = \mathcal{Q}(y^{ul}),$$

where  $\mathcal{Q}$  denotes quantization function. Subsequently, the  $l$ th RRH forwards  $\tilde{y}^{ul}$  to the baseband processing unit pool via its fronthaul link.

#### E. Compute-and-forward Relay (CoF)

Unlike DF relays, CoF relays do not decode individual transmitted messages. Instead, linear combinations of the received messages are decoded and forwarded by exploiting the broadcast nature of wireless channels [29], [86], [121], [113].

To illustrate the CoF mechanism, the multi-user multi-relay network model in [89] is considered, where  $L$  users communicate with a destination  $D$  via  $M$  relays. For the  $m$ th relay, the received signal is given by

$$y_m = \sum_{l=1}^L h_{ml}x_l + z_m, \quad m = 1, 2, \dots, M$$

where  $x_l$  is the transmitted signal,  $h_{ml}$  is the channel coefficients,  $z_m$  is the Gaussian noise, and  $y_m$  is a noisy linear combination of the transmitted signals through the channel. Subsequently, the CoF relay selects a scaling coefficient  $\alpha_m \in \mathbb{R}$  and an integer coefficient vector  $\mathbf{a}_m = (a_{m1}, a_{m2}, \dots, a_{mL})^T \in$

$\mathbb{Z}^L$  to decode the target signal  $\sum_{l=1}^L a_{ml}x_l$  from  $\alpha_m y_m$ . Formally, the decoder yields

$$\begin{aligned} \alpha_m y_m &= \sum_{l=1}^L \alpha_m h_{ml}x_l + \alpha_m z_m \\ &= \sum_{l=1}^L a_{ml}x_l + \sum_{l=1}^L (\alpha_m h_{ml} - a_{ml})x_l + \alpha_m z_m \end{aligned}$$

where  $\sum_{l=1}^L (\alpha_m h_{ml} - a_{ml})x_l$  is the error term arising from the mismatch between the channel and the selected integer coefficients, and  $\alpha_m z_m$  denotes the scaled channel noise. The decoded linear combination of the target signal, together with the coefficient vector  $\mathbf{a}_m$ , is then forwarded to the destination. Provided that these equations are linearly independent and sufficient in number (at least equal to the number of users), the original messages of all users can be recovered by solving the resulting system of linear equations.

Among the aforementioned relay types, AF relay is the most widely adopted relay type due to its accessibility and practical implementation [92], followed by DF and FF relays. From a mathematical perspective, the fundamental difference among these relay protocols lies in how they transform the signal and noise subspaces. AF models the relay as a linear operator (matrix multiplication) that scales both the signal and the additive channel noise, thereby introducing colored noise into the estimator. On the contrary, DF applies a hard nonlinear mapping (decoding and re-encoding) to regenerate a noise-free signal, effectively resetting the noise process at the cost of potential decoding errors. FF operates as a local stochastic estimator, computing the conditional expectation of the state before transmission, thus mathematically coupling the relay's local estimation error variance with the remote estimator. From an engineering standpoint, these differences dictate hardware complexity and spectral efficiency. AF is an analog *repeater* suitable for low-latency, low-cost hardware; DF functions as a digital *gateway* requiring substantial processing power for error correction; while FF acts as an *edge computing* node that distributes the computational load of estimation across the network. In contrast, CF and CoF schemes are primarily designed for physical-layer signal transmission, and their application to state estimation has remained largely unexplored. For the convenience of readers, we summarize the aforementioned relays in Table I from the perspective of complexity, noise propagation, latency, typical use cases, and limitations.

### III. RELAY-ASSISTED STATE ESTIMATION ALGORITHM

The adoption of relay-based protocols substantially alters signal transmission behavior and the performance landscape of networked state estimation, which poses considerable challenges in filter design and performance analysis. On the positive side, relays provide spatial diversity and geometric gain, extending the effective sensing range and maintaining observability even when direct sensor-to-estimator links are blocked. This leads to a higher probability of successful data delivery and improved estimation accuracy in large-scale deployments. However, these benefits come with inevitable trade-offs. The *two-hop* transmission introduces additional latency

TABLE I: A Comparison of Common Relay Strategies in Networked State Estimation

Relay	Complexity	Noise Propagation	Latency	Typical Use Cases	Limitations
<b>AF</b>	Low: Linear amplification only.	High: Amplifies both signal and channel noise (noise accumulation).	Low: Minimal processing delay (analog amplification).	Resource-constrained sensors; scenarios requiring low latency and simple hardware implementation.	Performance degrades significantly with distance due to noise amplification; sensitive to stochastic channel variations.
<b>DF</b>	High: Decoding and error correction mechanisms.	None: Eliminates noise accumulation by regenerating the signal.	High: Significant delay due to decoding and re-encoding processes.	Long-distance transmission; scenarios prioritizing link reliability over latency; systems with sufficient processing power.	High computational burden; potential for decoding errors which may lead to packet drops or error propagation.
<b>FF</b>	Medium/High: Running local filtering algorithms (e.g., KF) at the relay.	Low: Actively suppresses noise and disturbances through filtering in design before forwarding.	Medium: Delay depends on the convergence time and complexity of the local filter.	Distributed fusion architectures; scenarios requiring intermediate state estimates or preprocessing at the relay.	Requires knowledge of system models at the relay; increases computational load compared to AF.
<b>CF</b>	Moderate: Quantization and compression functions.	Moderate: Introduces quantization noise but avoids amplifying channel noise.	Medium: Latency introduced by quantization and compression logic.	Bandwidth-limited links; Cloud Radio-Access Networks; fronthaul links.	Performance depends heavily on the quantization resolution; introduces irreversible quantization errors.
<b>CoF</b>	High: Decoding linear combinations of messages (lattice codes).	Low: Manages noise via structured coding; exploits broadcast interference.	High: Complex decoding of linear equations introduces delay.	Multi-user multi-relay networks; interference-heavy environments where signals can be combined linearly.	Requires precise Channel State Information; application to state estimation is still largely unexplored; complex filter design.

and bandwidth consumption, which can degrade real-time performance. Furthermore, imperfect relaying introduces specific disturbances that inflate the estimation error covariance. Consequently, the optimal system design requires balancing the diversity gain from improved connectivity against the performance loss caused by relay-induced latencies and noise.

The mainstream filtering methods employed in relay-assisted frameworks can be broadly categorized into Kalman-type filtering,  $H_\infty$  filtering, moving horizon estimation (MHE) and set-membership filtering. These methods are designed to address different system complexities and practical constraints. The choice of algorithm typically depends on the noise characteristics and performance metrics. Kalman-Type Filtering including KF, EKF, UKF and CKF, is the dominant approach for stochastic systems with known statistical noise properties due to their theoretical rigor, engineering practicality and strong adaptability. In relay-assisted settings, UKF and CKF are particularly favored [49], [106] over EKF to handle the compound nonlinearities introduced by AF relaying without Jacobian linearization. When the statistical knowledge of relay channel noise is incomplete or the system is subject to energy-bounded disturbances,  $H_\infty$  filtering is widely adopted [78], [79]. It guarantees a worst-case disturbance attenuation level, ensuring robustness against relay-induced model uncertainties. Set-membership filtering offers a deterministic alternative by computing ellipsoidal sets that contain the true state [58] for scenarios where noise distributions are unknown but bounded. This is especially valuable in security-critical relay networks where non-stochastic attacks or biases render probabilistic assumptions invalid. To explicitly handle hard constraints on relay power and system states, MHE [110], [126] formulates

the estimation problem as a constrained optimization over a sliding window, albeit at a higher computational cost. The following subsections will review how these algorithmic frameworks are tailored to specific different situations.

To facilitate a better understanding of how the followed relay-assisted algorithms to be reviewed are implemented in practical applications, a general execution flowchart is presented in Fig. 4. The sensor first acquires measurements of the target system and then transmits them to the relay node. Upon receiving these imperfect measurements, which are transmitted via wireless channels potentially subject to network-induced phenomena and attack phenomena, the relay node processes them according to relevant protocols (e.g., AF, DF). Eventually, these signals are transmitted to either the remote estimator (for centralized state estimation) or the sensor node (for distributed state estimation). When the destination node receive the retransmitted signals, it performs operations such as filtering, fusion and control.

#### IV. RELAY-ASSISTED STATE ESTIMATION UNDER GENERAL DYNAMIC NETWORKED SYSTEMS

##### A. Nonlinear Systems

In networked state estimation, nonlinear systems constitute a central and extensively studied class. In many practical applications, such as power systems and motion tracking [5], the system dynamics or observation processes are inherently nonlinear, which necessitates the use of nonlinear estimation techniques. The typical nonlinear system model is as follows

$$\begin{aligned} x_{k+1} &= h(x_k) + w_k \\ y_{i,k} &= g_i(x_k) + v_{i,k}. \end{aligned}$$

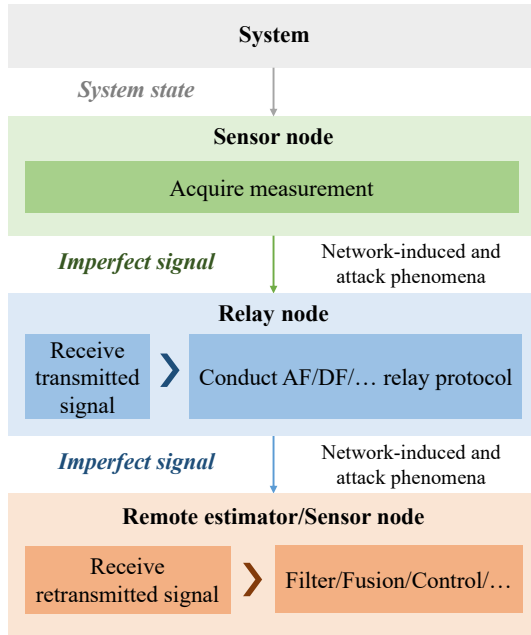


Fig. 4: A general execution flowchart of RASE algorithms in practical applications.

where  $k$  is the time instant,  $x_k$  is the system state and  $y_{i,k}$  is the measurement of  $i$ -th node.  $w_k$  is the noise in the process and  $v_{i,k}$  is the noise in the measurement.  $h(\cdot)$  and  $g_i(\cdot)$  stand for known nonlinear functions. Classical approaches such as the EKF rely on local linearization but require computationally expensive Jacobian calculations. The UKF and CKF improve estimation accuracy through sigma-point transformations, while PFs are capable of handling strong nonlinearity and non-Gaussian noise at the cost of increased communication and computational burden. These nonlinear estimation techniques have therefore been naturally adopted and extended to RASE, where relays are incorporated to improve communication reliability and system performance.

Several recent studies have demonstrated the integration of relays into nonlinear state estimation frameworks. Unlike direct sensing, the signal received by the estimator in a relay-assisted system is

$$z_k = \Theta(\Psi(\Upsilon(y_{i,k}))) \quad (1)$$

where  $\Upsilon(\cdot)$  indicates the pre-processing (e.g., local estimation, encoding) of  $y_{i,k}$ ,  $\Psi(\cdot)$  represents the relay protocol and  $\Theta(\cdot)$  denotes some post-processing (e.g., quantization, encryption) of the signal retransmitted by the relay. In [78], a distributed  $H_\infty$  fusion filtering algorithm has been investigated for nonlinear time-varying systems with packet losses and quantization over relay-assisted networks. AF relays have been employed to enhance communication reliability under missing measurements, while a dynamic quantization scheme has been introduced to reduce communication rates. Local filters have achieved prescribed  $H_\infty$  performance via recursive matrix inequalities, and a fusion center has combined local estimates through convex optimization. In [96], a recursive filtering method has been developed for nonlinear systems with full-duplex relays. In this framework, relay self-interference has

been explicitly addressed by modeling it as a component of the system noise. This treatment has improved estimation accuracy in simultaneous transmit-receive relay networks and highlighted the importance of accounting for relay-induced interference in estimator design. Moreover, in [76], a resilient recursive estimator has been designed for nonlinear time-varying systems under the DF relay mechanism. By placing a DF relay between the sensor and the estimator, analog noise accumulation has been mitigated and transmission errors have been corrected. Estimator-gain perturbations, such as rounding and aging effects, have been modeled as zero-mean random variables with bounded covariance. These uncertainties have been then accommodated within a resilient estimation framework, which guarantees an upper bound on the estimation-error covariance.

Classical nonlinear filters based on sigma-point techniques have also been extended to relay-assisted networks. In [106], a UKF-based approach is employed for full-duplex relay networks with binary encoding to reduce communication bandwidth. The modified UKF has explicitly handled quantization errors and self-interference while maintaining estimation accuracy. In [49], a multi-sensor CKF has been proposed for AF relay networks with random channel variations. Local CKFs have been executed at each sensor, and a covariance intersection strategy has been adopted at the fusion stage to combine estimates without requiring knowledge of cross-correlations, thereby ensuring robustness under channel uncertainty. These results have demonstrated that sigma-point filters remain effective in relay-assisted systems with limited or time-varying communication resources.

Advanced particle filtering techniques have further been developed for relay-assisted nonlinear estimation. In [60], an auxiliary particle filtering method has been introduced for multi-sensor networks using AF or DF relays. A likelihood function has been derived to characterize relay-induced effects such as channel fading and transmission noise. The resulting estimator has effectively addressed nonlinear and non-Gaussian estimation problems in relay networks and outperformed baseline filters, particularly under severe channel noise and fading conditions. Beyond model-based approaches, learning-based methods have also been explored. In [75], a neural-network-based estimator has been proposed for systems subject to measurement outliers in AF relay networks, where a neural network has been integrated to identify and compensate for outliers in relayed measurements by learning a nonlinear mapping from corrupted data to state estimates, thereby enhancing robustness and improving performance relative to conventional EKF- and UKF-based methods in outlier-dominated scenarios.

To provide a clear guide for algorithm selection in relay-assisted nonlinear estimation, the performance trade-offs of the aforementioned filters are summarized as follows. The EKF remains the standard choice for systems with mild nonlinearities and strict real-time constraints, yet it is prone to divergence when AF relays introduce compound nonlinearities (e.g., state-dependent channel noise) that violate local linearization assumptions. In such cases, Sigma-point filters (UKF, CKF) significantly outperform the EKF by capturing higher-order

moments of the relay-distorted signals without calculating Jacobians, making them particularly effective for handling the multiplicative noise inherent in AF protocols. Furthermore, PFs become indispensable in scenarios characterized by non-Gaussian channel noise or multi-modal distributions arising from severe fading and quantization, albeit at the cost of higher computational and communication burdens. Finally,  $H_\infty$  filters are preferred when the statistical properties of relay channel noise are uncertain or when robustness against energy-bounded disturbances is the priority

Overall, research on RASE for nonlinear systems has leveraged a broad range of nonlinear filtering techniques, including extended, unscented and cubature KFs, PFs, and neural networks. These approaches are designed to address relay-induced challenges such as quantization, fading, self-interference, disturbances, and outliers, while maintaining satisfactory estimation performance. The studies reviewed in this subsection illustrate the progress made toward robust and efficient nonlinear state estimation in relay-assisted networked systems and provide valuable insights for the development of future estimation strategies in increasingly complex communication environments.

### B. Complex Networked Systems

Complex networks, typically composed of a large number of nodes interconnected through intricate couplings, are widely encountered in power grids, biological networks, social networks, and related domains [31], [47], [103], [16], [19]. Compared with general nonlinear systems, complex networks exhibit richer dynamic behaviors and more intricate interconnections, which substantially increase the difficulty of state estimation. Its system model is typically exhibited as

$$\begin{aligned} x_{i,k+1} &= h(x_{i,k}) + \sum_{j=1}^N \omega_{ij} \Gamma x_{j,k} + w_{i,k} \\ y_{i,k} &= C_{i,k} x_{i,k} + v_{i,k} \end{aligned}$$

where  $x_{i,k}$  is the system state of the  $i$ -th node,  $y_{i,k}$  is the measurement output,  $h(\cdot)$  a known nonlinear function, and  $w_{i,k}$  and  $v_{i,k}$  are process noise and measurement noise, respectively.  $W = [\omega_{ij}]$  is the coupled configuration matrix of the network.  $\Gamma$  is an inner-coupling matrix. When relays are introduced to assist state estimation in complex networks, from (1) it can be seen that the network topology and coupling structure must be explicitly incorporated into estimator design, thereby introducing additional layers of complexity. As a result, state estimation for relay-assisted complex dynamic networks has attracted increasing research attention.

For AF-assisted networks with quantized sensing, a UKF framework has been proposed in [64]. In this framework, quantization has been employed to compress large-scale sensor data and significantly reduce communication overhead. The resulting UKF-based estimator has explicitly addressed both quantization errors and relay-induced noise amplification, with filter gains optimized by minimizing an upper bound on the estimation error covariance. It has been shown that, even under the combined effects of quantization, random relay gains,

and system nonlinearity, reliable estimation performance is maintained and mean-square error boundedness is guaranteed under mild conditions.

When uniform quantization coexists with missing measurements at the node-to-node layer, a two-step AF-assisted recursive estimator has been developed for coupled complex networks [35]. In this work, missing data have been modeled by Bernoulli processes, and AF relays operate on the sensor-to-estimator links with random transmission power. By optimizing a variance-constrained index, a tunable upper bound on the state-error covariance has been obtained. Moreover, a monotonic relationship between the minimized bound and the missing probability has been established, which quantitatively links communication unreliability to estimation quality.

Beyond second-order performance criteria, non-Gaussian disturbances and uncertain inter-node couplings motivate robust information-theoretic designs. In [72], a maximum correntropy criterion (MCC)-based estimator has been developed for complex networks with randomly varying channel gains, uncertain internal couplings, and non-Gaussian noise over AF relay links. By replacing conventional quadratic criteria with MCC and employing a fixed-point iterative algorithm with guaranteed convergence, this approach has effectively handled relay-amplified noise and coupling uncertainties while outperforming traditional Kalman-type filters.

Scheduling and bandwidth constraints inherent in complex networks can also be incorporated into estimator design through stochastic traffic models. In [63], an EKF-type recursive filter has been proposed for AF-assisted networks operating under token-bucket communication protocols. The results have demonstrate that, as the average successful transmission rate increases, the upper bound of the estimation error covariance decreases, even in the presence of relay-induced noise amplification and protocol-induced irregular sampling. Measurement degradation caused by long-range wireless propagation has further been addressed by modeling sensor-side transmission energy, relay-side transmission energy, and channel degradation as random processes. Under this setting, an EKF-based estimator tuned via Riccati-like recursions has been constructed, ensuring mean-square exponential boundedness [73].

In addition to AF-based protocols, DF relays have been investigated for state estimation in nonlinear complex networks with stochastic couplings [80]. In such systems, inter-node coupling strengths vary randomly according to prescribed probability distributions, capturing uncertainties commonly observed in neural and communication networks with randomly weighted connections. The DF strategy improves communication reliability by decoding signals prior to retransmission, thereby avoiding the noise amplification inherent in AF relays. The associated estimator explicitly incorporates stochastic coupling models into the nonlinear dynamics and establishes sufficient conditions for the stability of the estimation error system.

In summary, recent research on RASE for complex networked systems has addressed key challenges arising from uncertain couplings, randomized network structures, quantization effects, and protocol-induced communication irregularities.

The reviewed studies have demonstrated that, by combining robust filtering principles such as MCC, UKF, and EKF with practical relay strategies and communication protocols, accurate and resilient state estimation can be achieved in large-scale complex networks. These developments have indicated the growing maturity of relay-assisted estimation frameworks and their potential for future intelligent infrastructure applications.

### C. Other Specific Systems

In addition to nonlinear and complex networks, many relay-assisted estimation problems are driven by specific system structures or operational constraints, which substantially reshape filter design. The following representative studies illustrate how estimators in RASE have been designed for particular system classes to maintain stability and accuracy.

In [107], recursive filtering has been investigated for 2-D systems with AF relays under degraded measurements and dynamic biases. In this setting, the 2-D state evolves along two coupled dimensions, while the relay amplifies and forwards both signals and channel noise. The estimator has augmented the state with a bias component and has incorporated relay effects through modified measurement gains and covariances. By deriving an upper bound on the error covariance and minimizing it recursively, estimation accuracy has been maintained. For nonlinear bias-corrupted systems, a dynamic event-triggered mechanism combined with a variable-gain AF relay has been developed in [14] to reduce communication load and enhance signal quality. The proposed filter has minimized the error-covariance bound at each step, enabling simultaneous state and bias estimation while ensuring mean-square exponential boundedness under efficient triggering.

The recursive quadratic filtering problem has been addressed in [108] for linear stochastic systems subject to dynamical bias, non-Gaussian noises, and AF relays with random transmission powers. An augmented state model incorporating both the original state and bias, together with their second-order Kronecker products, has been used to reformulate the quadratic estimation problem into a linear filtering form. A recursive filter has been designed to minimize the error covariance via an optimal gain, and boundedness conditions have been established under non-Gaussian noise and stochastic relay effects. Complementary to these bias-augmented designs, a distributed 4-bit Kalman filtering strategy has been developed in [52] for random-parameter 2-D systems with measurement censoring. In this work, AF relays have been combined with a stochastic communication protocol to regulate channel access. By deriving the conditional expectation and variance of censored measurements under the AF and stochastic communication protocol, each local filter has fused its own and neighbors' information over a known topology and has minimized an upper bound on the filtering error variance. Simulation results have validated the approach and have quantified the impact of relay power, channel coefficients, and censoring thresholds on estimation accuracy.

Robust recursive filtering has been studied in [95] for linear stochastic systems with parametric uncertainties, where an AF relay has been employed between the sensor and the

remote filter. A robust recursive filter has been constructed using average transmission power, and an upper bound on the error covariance has been derived and minimized online. Mean-square boundedness of the estimation error has been established. In another representative contribution [32], an optimized distributed filter has been investigated for time-varying state-saturated systems using AF relays and a dynamic event-triggered mechanism, with transmission powers modeled as random variables. Without state augmentation, saturation has been linearized via a mean-value lemma and represented as a diagonal gain, enabling tractable recursion of the error dynamics. An upper bound matrix (UBM) for the error covariance has been derived, and distributed filter gains have been obtained by minimizing the trace of the UBM, ensuring boundedness.

In summary, these studies have suggested several core principles for specialized relay-assisted estimation. First, system states should be augmented and regularized by explicitly modeling dynamic biases and delays, while conservative covariance shaping is employed to absorb relay-induced distortions. Second, the relay strategy should be aligned with the operational regime: DF relays are preferable when hop noise dominates and sufficient processing capability is available, whereas AF relays are more suitable when low latency and implementation simplicity are critical.

## V. RELAY-ASSISTED STATE ESTIMATION WITH NETWORK-INDUCED PHENOMENA

In practical applications, various uncertainties such as sensor aging or failure, limited bandwidth, and external environmental disturbances give rise to multiple network-induced phenomena in networked systems, including communication noise, data loss, time delays, bit flips and observation attenuation [20], [12]. These effects may lead to incomplete data acquisition by sensors and consequently degrade the overall system performance. Addressing network-induced phenomena therefore constitutes a central research challenge in state estimation. The primary objective lies in developing estimation methods that mitigate these adverse effects so as to enhance global estimation accuracy and prolong network lifetime. In relay-assisted networked state estimation, the introduction of relays creates both new opportunities and additional challenges for estimator design under network-induced constraints. The following discussion elaborates on these issues by focusing on three representative types of network-induced phenomena. These phenomena can be mathematically unified into a generalized signal model. Let  $s_k$  be the ideal signal. The actual signal  $\tilde{s}_k$  received by the estimator can be modeled as:

$$\tilde{s}_k = \sum_{l=0}^{\tau_{max}} \alpha_{k,l} \Lambda_k s_{k-l} + v_k.$$

$v_k$  indicates the channel noise.  $\alpha_{k,l}$  is a Bernoulli variable which describes the packet losses phenomenon. If  $\alpha_{k,l} = 0$ , the packet is dropped. The random matrix  $\Lambda_k$  representing multiplicative channel gains models the fading channel. The communication delay is represented by the delayed terms  $s_{k-l}$ , where the measurement received at time  $k$  may effectively correspond to the state at  $k-l$ .

### A. Fading Channels

Fading refers to the phenomenon whereby wireless signals experience time-, space-, or frequency-selective fluctuations in amplitude and phase during propagation, caused by multipath scattering, obstacle-induced shadowing [8], bandwidth dispersion [26], and random environmental variations [114]. In practice, fading encompasses both small-scale effects, such as rapid multipath fading modeled by Rayleigh or Rician distributions, and large-scale shadowing, which is often modeled by log-normal processes. It may be flat or frequency-selective, slow or fast, and spatially or temporally correlated across links. In relay-assisted networked estimation, fading enters measurement and communication models as multiplicative uncertainties, rendering the effective measurement matrices and noise covariances time-varying random variables. In multi-hop architectures, these effects are compounded through products of per-hop fading gains, while imperfect channel state information (CSI) introduces further model mismatch. Together, these mechanisms degrade observability, inflate estimation error covariances, and may destabilize classical Kalman-type estimators unless fading is explicitly modeled and mitigated.

Building on the above understanding, fading in relay-assisted estimation has been addressed through two complementary modeling perspectives. From a packet-centric viewpoint, each hop has been modeled by time-varying reception probabilities that depend on instantaneous channel gains and transmission power under block-fading assumptions [45]. Measurement recoverability has been characterized by Boolean variables representing successful direct receptions and relay transmissions, and Kalman filtering has been performed using only successfully recovered data. Estimation performance has been evaluated through the expected one-step error covariance. Within this framework, increasing the packet arrival probability on any link has been shown to improve estimation performance, motivating joint optimization of relay configurations and transmission powers. Although the resulting two-step optimization strategy (i.e., selecting relay configurations under equal power and then refining power allocation) has been nonconvex, it has achieved near-optimal performance in practice. Closely related to this approach, predictive power control has been formulated as a stochastic model predictive control problem in [128], where sensor and relay transmission powers have been dynamically adjusted to balance energy consumption against estimation accuracy under fading-induced packet losses.

From a gain-centric perspective, in [24], fading effects have been explicitly modeled as diagonal random channel-gain matrices that directly affect transmitted state estimates. MMSE encoders and AF relay matrices have been designed to compensate for multiplicative channel distortions, while binary measurement outcomes have been incorporated through their conditional expectations. Local estimation performance has been guaranteed via sufficient conditions for mean-square exponential boundedness, and distributed filter gains have been obtained through linear matrix inequality (LMI)-constrained optimization. In a related study, recursive fusion estimation under centralized multi-sensor systems with AF relays has

been investigated in the presence of random bit-flip phenomena [123]. Collectively, these channel-aware mechanisms have preserved observability and have controlled estimation error covariances in multi-hop fading networks.

Beyond explicit relay modeling, fading channel characteristics themselves have been exploited in estimator design. In [25], Rayleigh fading has been modeled using random diagonal gain matrices, and amplitude distortions have been corrected via linear transformations based on mean channel gains prior to filtering. Combined with a binary-measurement treatment that separates mean components from zero-mean residuals, a distributed filtering scheme has been derived using recursive linear matrix inequalities. The resulting error dynamics have been shown to be exponentially ultimately bounded in the mean-square sense, and the framework has been readily extended to multi-hop and relay-assisted architectures. Along similar lines, fading, AF relays, and binary measurements have been jointly considered in a consensus-based estimation framework in [68]. A Kalman-consensus filter with measurement reorganization has been designed, achieving linear-unbiased minimum-variance fusion over sensor-relay-estimator links. The associated estimator gains have been computed via Riccati-type recursions that simultaneously account for fading and transmission delays.

In addition to Kalman-type estimators, optimization-based techniques and full-duplex relaying have provided additional tools for fading mitigation. A moving-horizon estimation (MHE) scheme for filter-and-forward (FF) full-duplex relays has been proposed in [110]. In this framework, the relay preprocesses and forwards sensor signals while explicitly modeling fading and the self-interference inherent in full-duplex operation. The co-designed MHE schemes at the relay and at the remote estimator have accommodated channel effects and self-interference-induced delays within the optimization horizon, thereby improving robustness under uncertain interference statistics.

Overall, fading in RASE can be addressed either as random packet arrivals governed by instantaneous signal-to-noise ratios (*packet-centric*) or as multiplicative random gains affecting transmitted estimates (*gain-centric*). Both perspectives have led to explicit channel-aware strategies, including relay selection, coding, and power control in packet-centric formulations, as well as MMSE encoder and relay design with local performance guarantees in gain-centric approaches. Their applicability varies depending on the practical communication architecture and signal processing requirements. The packet-centric model is practically suitable for digital communication networks employing error detection mechanisms (e.g., Cyclic Redundancy Check), where deep fading events cause decoding failures that result in complete packet erasures. This binary abstraction simplifies the physical layer into probabilistic discrete events. In contrast, the gain-centric model is indispensable for analog AF relay systems or scenarios where *soft* information is preserved. In such cases, signals are distorted rather than discarded, requiring the estimator to explicitly compensate for continuous amplitude attenuation and phase rotation to maintain observability. These strategies play a crucial role in maintaining observability and constraining estimation error

covariances in multi-hop relay-assisted networks subject to fading impairments.

### B. Communication Delays

In networked state estimation, communication links are frequently affected by electromagnetic interference, sensor-side processing limitations, and bandwidth constraints, all of which may induce stochastic communication delays. Such delays are typically categorized into measurement (sensor-to-estimator) delays, where observations are received with latency, and inter-sensor or multi-hop transmission delays [62], which arise during forwarding, fusion, or consensus operations. Both forms degrade estimation performance by weakening effective observability, inflating error covariances, and generating out-of-sequence measurements. In relay-assisted architectures, per-hop buffering and relay-side processing further compound end-to-end latency, so that the effective measurement model often takes a delayed form as  $y_k = \tilde{C}_k x_{k-d_k} + \tilde{v}_k$ , where the delay  $d_k$  is random, and the effective gains and noise  $(\tilde{C}_k, \tilde{v}_k)$  are altered by relay operations.

Delays in relay-assisted estimation have been most effectively handled by explicitly modeling how latency reshapes the usable observation sequence and by designing delay-aware filters that preserve mean-square stability. Encoding-decoding-based fusion estimation with filter-and-forward (FF) relays under stochastic measurement delays has been investigated in [61], where delays have been modeled by Bernoulli random variables. In this framework, local relay filters have been introduced to recursively minimize upper bounds on the estimation error covariance, and encoded estimates have been transmitted to the fusion center through probabilistic quantization. This design has coupled delay effects with packet uncertainty and has demonstrated that delay-compensated relay filtering can stabilize estimation even when multiple hops experience random latency.

Building on the above direction, a stubborn state estimation framework for time-delay systems with half-duplex (HD) relay communication has been developed in [43]. In HD networks, the relay alternates between reception and transmission, which naturally introduces a two-step periodic delay in the communication loop. The corresponding signal scheduling has been explicitly modeled, and LMI-conditions have been derived to ensure that both the filter-and-forward relay and the remote estimator achieve ultimate boundedness of the estimation error in the presence of time delays and measurement outliers. The analysis has shown that delay characteristics are tightly coupled with the relay operating mechanism: although the HD mode avoids self-interference, it effectively doubles the end-to-end latency and must therefore be compensated through adaptive gain design and innovation-saturation strategies.

In a complementary line of work, a consensus Kalman filter for AF relay networks subject to heterogeneous transmission delays and fading channels has been developed in [65]. By reorganizing delayed observations into equivalent delay-free sequences, optimal Kalman-consensus gains have been derived via coupled Riccati-Lyapunov equations. The resulting filter has guaranteed convergence even when individual relay links

exhibit distinct delay and packet-loss characteristics, indicating that consensus mechanisms can restore global observability and robustness against asynchronous data arrivals. Extending to a practical application scenario, recursive filtering for power harmonic detection in AF relay networks with stochastic communication delays has been addressed in [50]. Random delays have been modeled using Bernoulli sequences, and a delay-dependent recursive filter has been designed to minimize an upper bound on the estimation error covariance, thereby enabling real-time adaptation to time-varying delay distributions and relay power fluctuations.

Overall, the existing body of work has established that communication delays in relay-assisted networked estimation are not merely secondary disturbances but intrinsic design factors. Accurate modeling and compensation of stochastic and structural latencies are essential for preserving estimation accuracy, particularly in large-scale sensor-relay-estimator networks operating under bandwidth, interference, and synchronization constraints.

### C. Packet Losses

In packet-switched communication systems (e.g., TCP and UDP), unreliable links, external interference, and sensor aging or failures routinely induce packet dropouts in networked state estimation. If such losses are ignored, estimation performance can be severely degraded by disrupting information flow required for observability and by inflating estimation error covariances. In relay-assisted architectures, packet dropouts occur on a per-hop basis and interact with relay protocols, further complicating estimator design. A commonly adopted model introduces a reception indicator  $\gamma_k \in \{0, 1\}$ , typically governed by Bernoulli or Gilbert-Elliott processes, such that  $y_k = \gamma_k \tilde{C}_k x_k + \tilde{v}_k$ . Effective estimation strategies therefore combine explicit loss modeling with suitable filtering schemes and, where possible, co-design relay gains to balance signal-to-noise ratio and packet arrival rates.

Building on the above modeling framework, relay channels with packet losses have been widely represented by per-hop Bernoulli switches. In earlier studies, relay operation over packet-dropping links with multiple sensors has been examined in [44], where alternative strategies (e.g. forwarding data from a single sensor, switching between sensors, or performing linear network coding) have been analyzed. By deriving upper bounds on the expected estimation error covariance, operating regions favoring each strategy have been characterized and validated through simulations. This perspective of optimizing relay transmission decisions under packet losses aligns naturally with finite-horizon and moving-horizon estimation paradigms.

In relay-assisted systems employing AF protocols, packet losses on sensor-to-relay and relay-to-estimator links have been modeled by independent Bernoulli processes in [79]. In this setting, end-to-end measurements reach the estimator only when both hops succeed. The estimator update has been formulated using mean success probabilities and average transmission energies, while stochastic packet arrivals have entered the error dynamics as multiplicative disturbances. A

finite-horizon  $H_\infty$  filtering design has been developed by solving coupled backward Riccati difference equations, yielding time-varying gains and guaranteeing finite-horizon disturbance attenuation in the presence of packet losses. In a related direction, time-varying nonlinear systems over half-duplex AF networks with multiple Bernoulli loss processes have been investigated in [42]. An  $H_\infty$  estimator has been synthesized via recursive linear matrix inequalities, providing constructive feasibility conditions and clarifying the impact of half-duplex scheduling and per-hop reception probabilities on robustness margins. Furthermore, packet dropouts and AF relays have been incorporated into a unified switching-model framework for fuzzy proportional-integral observers in multirate nonlinear systems in [104]. In that work, proportional and integral gains have been determined through convex optimization to enforce an  $H_\infty$  performance level under relay-induced uncertainties and stochastic losses, demonstrating compatibility with non-classical observers and multirate architectures.

FF relays have also been exploited to improve the effective signal-to-noise ratio of forwarded information under packet loss. A moving-horizon estimation (MHE) framework for relay-channel-based systems with multi-hop packet losses has been proposed in [126], where three Bernoulli sequences have been used to model losses on sensor-relay, relay-estimator, and direct links. By reformulating the maximum a posteriori estimation problem into a receding-horizon optimization, sufficient conditions for mean-square ultimate boundedness of estimation errors have been established. The results have shown that both the horizon length and relay reliability jointly determine achievable estimation accuracy in loss-prone environments. Moreover, recursive state estimation for 2-D nonlinear systems with packet losses over DF relay channels has been investigated in [105]. In that study, DF relays have been employed to extend communication under limited sensor capability, while packet dropouts have been modeled by Bernoulli sequences. A local minimum-variance estimator has been designed to minimize an upper bound on the error variance at each step, and the effects of packet arrival rates and quantization levels on estimation accuracy have been analyzed.

Taken together, the above studies have demonstrated that effective RASE under packet losses relies on explicit dropout modeling combined with finite-horizon robust or moving-horizon estimation techniques. When such estimators are co-designed with relay strategies and communication parameters, stability and estimation accuracy can be preserved even in networks subject to severe and persistent packet losses.

Despite the aforesaid substantial achievements, the development of a unified modeling framework for relay-assisted networked systems that incorporates multiple network-induced phenomena under diverse communication mechanisms remains an open and attractive research topic [71], [83], [30], [70].

## VI. ENERGY MANAGEMENT IN RELAY-ASSISTED STATE ESTIMATION

In practical applications, relay-assisted networked state estimation systems often perform monitoring and tracking tasks

for highly mobile targets over large geographical regions. Components such as sensors, relays, and remote fusion estimators are typically deployed in vast and harsh environments, where they rely solely on battery power for operation. Under these conditions, battery replacement is extremely difficult, and in many cases impractical. During state estimation, electrical energy is consumed by sensing, relay signal processing, data fusion at remote estimators, and communication among network components. Consequently, efficient utilization of finite energy resources to prolong network lifetime has become a central research issue in RASE. A natural response has been the co-design of energy scheduling and energy harvesting (EH) strategies, subject to energy-causality constraints and battery dynamics, together with relay protocols and estimator performance objectives.

Motivated by the above considerations, energy has been treated as a first-class constraint in recent relay-assisted estimation studies, and estimator recursions, transmission scheduling, and EH mechanisms have been jointly designed to guarantee estimation performance under energy causality. A representative recursive framework has been proposed in [88], where DF relays equipped with EH capability at both sensors and relays have been considered. A time-varying estimator has been derived by minimizing an analytical upper bound on the estimation error covariance. Uniform boundedness of the estimation error has been established, and monotonic improvement of the bound with increasing transmission probability has been demonstrated, thereby explicitly linking energy availability to estimation performance. In a related recursive framework, stochastic nonlinear plants over AF relay links with EH at both sensors and relays have been investigated in [10]. Random per-hop transmission powers, one-step autocorrelated process noises, two-step cross-correlated measurement noises, and autocorrelated channel noises have been explicitly modeled. A unified recursive filter has been developed whose gain minimizes, at each step, a guaranteed upper bound on the second-moment error matrix, and boundedness has been analyzed. EH processes have entered the model through tractable formulations governing binary transmission-availability indicators at each hop. It has been shown that EH-aware relay-assisted estimation remains stable even when noise and channel disturbances exhibit temporal correlation, while capturing stochastic power availability at both nodes.

From the perspective of energy scheduling, two main research directions have emerged. In one direction, two-hop DF relay networks with explicit EH batteries have been studied, and joint sensor-relay power control has been formulated as a cooperative decision process aimed at minimizing the estimation error covariance under battery dynamics [115]. Battery evolution has been modeled via a “harvest-and-charge then spend” mechanism, and joint power actions have been selected based on system states, leading to a Markov decision framework that respects energy causality while optimizing estimation accuracy. Energy harvesting with energy sharing between sensor and relay has been further examined in [118], where both nodes draw energy from a common time-varying source under per-transmission energy constraints. Packet arrivals at each hop have been modeled by Bernoulli pro-

cesses, and dynamic programming has yielded simple battery-dependent transmission policies. In particular, event-triggered and threshold-based strategies have been derived to balance energy consumption against the expected estimation benefit of successful end-to-end transmission.

When EH is absent or abstracted as a fixed energy budget, optimal offline power and time scheduling have also been investigated. Under finite horizons and limited total energy, a converted-table method has been developed to minimize average estimation error by judiciously interleaving high-power (high-reliability) and low-power (drop-prone) transmissions [23]. High-power usage has been distributed as uniformly as possible over time and across relays, and optimality has been established under the assumed model. Channel-aware energy management has been further addressed in [66], where two-hop networks with time-varying channels have been considered. In this framework, packet success probabilities depend jointly on channel states and selected energy levels, and the resulting estimation-energy co-optimization has yielded optimal deterministic stationary policies with clear threshold structures. These policies specify that transmission should occur only when the estimator's update urgency, measured by the elapsed time since the last successful transmission, exceeds a channel-dependent threshold and sufficient local energy is available. Both low- and high-energy transmission modes have been incorporated, and the trade-off between estimation quality and energy expenditure has been explicitly quantified.

Across the aforementioned studies, a consistent framework for energy-aware RASE has emerged. Battery dynamics, EH processes, and energy-causality constraints are explicitly incorporated at both sensors and relays. Performance-driven joint optimization of transmission power and scheduling is performed in conjunction with relay protocol characteristics (such as noise amplification in AF relays and decoding reliability in DF relays), which plays a crucial role in achieving long network lifetime while maintaining satisfactory estimation accuracy. Moreover, it is worth noting that in practical scenarios, relays are not only energy-limited but also quantity-limited [112], [74], [41]. Hence, they also should be dynamically scheduled to maximize utilization while improving estimation accuracy. However, existing studies that explicitly address relay scarcity have remained relatively limited.

## VII. SECURITY OF RELAY-ASSISTED STATE ESTIMATION

### A. Eavesdropping

In networked state estimation, wireless communication is widely adopted due to its flexibility, while the openness of the medium renders such systems vulnerable to eavesdropping. Adversaries may intercept transmitted signals to infer sensitive system information, which can subsequently facilitate more disruptive attacks and degrade estimation performance. These risks are amplified in relay-assisted architectures, where information is transmitted over multiple hops using diverse relay protocols. Eavesdropping may occur on the sensor-relay link, the relay-estimator link, or both. In amplify-and-forward (AF) relays, both signal and noise are forwarded, thereby

modifying the effective signal-to-noise ratio available to an adversary, whereas decode-and-forward (DF) relays may expose decoded information if interception occurs after decoding. Consequently, estimation strategies, transmission scheduling, and protection mechanisms must be jointly designed to ensure that the legitimate estimator achieves satisfactory accuracy while the inference capability of an eavesdropper remains fundamentally constrained.

In recent years, several relay-assisted estimation schemes under eavesdropping have been proposed. A scheduling-centric approach has been developed in [116], where an eavesdropper independently intercepts each hop according to Bernoulli processes with given success probabilities and applies MMSE recursion upon successful interception. Under this model, symmetric two-hop communication graphs are formed for both the legitimate estimator and the eavesdropper, while packet reception outcomes remain statistically independent. Transmission decisions at the sensor and relay have been jointly determined based on acknowledgment feedback, and a finite-horizon objective has been formulated to minimize the covariance trace of the legitimate estimator while maximizing that of the eavesdropper. The resulting optimal policy has exhibited a threshold structure in the covariance states of the relay, the estimator, and the eavesdropper. In the infinite-horizon setting, it has been shown that certain threshold policies keep the expected estimation error of the legitimate estimator bounded while forcing the eavesdropper's error to diverge, provided that each eavesdropping probability is strictly less than 1.

In contrast to scheduling-centric designs, a protection-centric method has been introduced in [127], where encryption and decryption mechanisms are embedded into the relay-assisted estimation process. In this architecture, measurements are linearly encrypted with artificial noise prior to transmission, and decryption is performed only after the relay-estimator hop, which may itself be subject to packet losses. A decryption-free relaying protocol has been employed to prevent information leakage at the relay. Under this framework, matrix equality and inequality conditions have been derived to ensure that the decryption error remains unbiased and uniformly mean-square bounded upon successful packet arrival. These conditions have further enabled the construction of a recursive Kalman-type estimator with a guaranteed upper bound on the conditional estimation error variance, thereby establishing boundedness of the estimation error under eavesdropping threats.

### B. Denial-of-service Attack

Another salient security risk in networked state estimation is the denial-of-service (DoS) attack, in which an adversary intentionally disrupts wireless communication links so that otherwise valid packets fail to reach their destination, potentially crippling the communication backbone [9], [28]. In relay-assisted architectures, the attack surface is further expanded, since jamming may target the sensor-relay hop, the relay-estimator hop, or both. Robust estimation designs therefore require the joint optimization of transmission scheduling, relay

selection, and power control to preserve mean-square stability and to keep the estimation error covariance bounded under admissible attack rates.

In relay-assisted remote estimation under DoS attacks, jamming has commonly been modeled as additional interference power injected into each communication hop, which degrades the signal-to-interference-plus-noise ratio (SINR). The resulting SINR reduction increases the symbol error rate (SER) and thus lowers packet reception probabilities. Since successful end-to-end transmission depends on the outcomes of both hops, packet losses directly influence the estimation error dynamics. Within this framework, the interaction between a relay and a resource-constrained attacker has been formulated as a zero-sum stochastic game in [117]. Transmission and jamming power levels have been selected by the legitimate system and the attacker, respectively, while system states have incorporated battery energy levels and recent estimation error covariances. The payoff function has captured the trade-off between estimation quality and energy consumption. As closed-form equilibria were intractable, a stationary optimality equation has been derived, and Nash equilibria have been obtained using Q-learning.

Complementary analysis of attacker energy allocation across two hops has been conducted in [81]. Under fixed network topology and identical channel conditions, jamming either hop has been shown to exert equivalent influence on both terminal and average estimation errors. The trade-off between jamming frequency and jamming power has been further analyzed. For systems with normal plant matrices, closed-form expressions for terminal and average estimation errors have enabled single-variable optimization. For more general plant dynamics, an optimal attack scheduling algorithm has been developed by iterating over the number of attacks and optimizing the per-attack jamming power.

Beyond battery-limited single-attacker models, DoS scenarios with energy-harvesting adversaries have been investigated. In [18], coordinated attackers equipped with energy harvesting capability have mounted DoS attacks over a two-hop relay network. The problem has been formulated as a cooperative multi-agent Markov decision process, where harvested energy, battery states, and estimator error covariances evolve jointly. An SER-SINR mapping has linked jamming power to per-hop packet reception probabilities, and a Q-learning-based solution has yielded optimal jamming power policies. A key insight has been obtained that decentralized implementation is possible by using local action-value functions at each attacker without sacrificing global optimality. This work extends earlier studies by moving from fixed energy budgets to stochastic energy inflow and from single to multiple coordinated attackers [81].

In addition, multi-sensor two-hop systems operating under round-robin (RRP) medium access have been studied in [124] in the presence of DoS attacks. An attacker with limited energy and a finite attack budget has been shown to exploit the transmission schedule to maximize estimation degradation. By introducing per-hop packet-arrival matrices and deriving a probabilistic Riccati recursion under RRP, the average estimation error covariance has been characterized, and an optimal finite-horizon DoS schedule explicitly accounting for the relay

stage has been obtained. The analysis has revealed how channel selection probabilities, relay placement, and attack timing jointly shape system performance.

Beyond pure DoS attacks, resilience against hybrid threats has been addressed through relay-side processing. In [51], filter-and-forward (FF) relays have been employed in a defense architecture where each relay performs local filtering prior to forwarding and the remote estimator executes sequential fusion. Hybrid attacks, including DoS and false data injection, have been modeled by multiple independent Bernoulli processes acting on sensor-relay and relay-estimator links, together with random transmission powers. Relay-side recursive filters and a sequential fusion estimator have been designed, and sufficient conditions have been derived to guarantee mean-square boundedness of both local filtering errors and global estimation errors. These results indicate that FF relays can enhance resilience by improving signal quality before vulnerable hops and enabling principled fusion under simultaneous DoS and data integrity attacks.

Overall, existing studies have suggested two complementary strategies for countering DoS attacks in RASE. One strategy relies on game-theoretic power control and scheduling to maintain estimation performance under probabilistic link blocking. The other focuses on attacker energy allocation analysis to identify when hop selection is critical and how jamming frequency and intensity influence both terminal and average estimation errors. Together, these approaches provide systematic tools for designing resilient relay-assisted estimation systems under adversarial communication disruptions.

## VIII. CONCLUSIONS AND FUTURE TOPICS

This paper has provided a comprehensive review of relay-assisted networked state estimation, covering modeling principles, algorithmic developments, and system-level integration. Estimator design for nonlinear, complex, and structure-constrained systems has been examined, with emphasis placed on how classical and modern filtering techniques have been adapted to relay-assisted settings. Network-induced phenomena, including fading channels, communication delays, and packet losses, have been analyzed, and the ways in which relay protocols reshape effective measurement models and estimation error dynamics have been clarified. Energy management and energy harvesting issues, together with security considerations, have also been discussed, highlighting the necessity of jointly designing sensing, relaying, and estimation mechanisms to achieve a balanced trade-off among estimation accuracy, latency, energy efficiency, and confidentiality.

Based on the reviewed literature, several promising research directions are identified for future investigation:

- 1) **Integration with Integrated Sensing and Communication (ISAC):** In next-generation networks [53], relay nodes will likely function simultaneously as communication relays and active sensors. Investigating ISAC-enabled relay-assisted estimation is a vital frontier. Research is needed on ISAC-enabled relays. A major technical challenge involves the design of dual-functional waveforms that minimize the mutual interference between sensing

and communication subspaces. Furthermore, jointly optimizing the power allocation for sensing beams and relaying links typically results in non-convex optimization problems that are computationally prohibitive for real-time implementation[77].

- 2) Task-Oriented Relaying and Edge Intelligence: Existing relay strategies primarily focus on signal fidelity[48]. However, in resource-constrained large-scale systems, relays should evolve towards semantic-aware and task-oriented processing. Future research should explore semantic-aware processing. The primary technical challenge here lies in mathematically quantifying the *semantic value of information* relevant to the estimator. Unlike Shannon capacity which focuses on bit recovery, constructing optimization frameworks that trade off semantic fidelity against computational delay on resource-limited relay hardware remains an open problem.
- 3) Resilience Against Intelligent and Learning-Based Attacks: As adversaries increasingly utilize machine learning to launch sophisticated attacks (e.g., intelligent jamming or stealthy model poisoning)[109], [99], [22], [57], traditional robust filtering may fall short. A critical open challenge is the design of proactive defense mechanisms where the estimator and relays play a dynamic game against intelligent attackers. Developing reinforcement learning-based defense strategies is a priority. However, this introduces significant technical hurdles, specifically in modeling high-dimensional stochastic games with incomplete information. Proving the convergence of learning algorithms when both the attacker and the defender are adapting their policies in a non-stationary environment constitutes a formidable theoretical obstacle.

Ultimately, beyond these theoretical challenges, a concerted effort is needed to bridge the gap between algorithmic design and practical engineering, as only a limited number of preliminary investigations have been reported. Future work should focus on applying and validating these relay-assisted frameworks in diverse real-world application domains, such as unmanned aerial vehicle (UAV) swarms [119], energy transmission systems [111] and industrial automation systems [11], to verify their robustness under physical hardware constraints.

#### Disclosure statement

No potential conflict of interest was reported by the author(s).

#### Data availability statement

Data will be made available on reasonable request.

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