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Cooperative Event-Triggered Forwarding with Compressed Sensing in Multi-Hop Wireless Sensor Networks

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Abstract: To address the degradation of state estimation accuracy induced by channel fading in multi-hop wireless sensor networks, this paper proposes a novel approach that integrates cooperative communication, compressed sensing and an event-triggered forwarding strategy. By introducing cooperative relay nodes at the forwarding layer, the proposed method leverages spatial diversity gain to enhance the packet arrival rate γ_k^i. Simultaneously, compressed sensing is utilized to reduce the payload volume, which, combined with the event-triggered forwarding strategy to mitigate unnecessary transmissions, achieves a dual optimization of energy efficiency and reliability. Simulation results demonstrate that under low signal-to-noise ratio channel conditions, the proposed strategy significantly improves system stability while maintaining low energy consumption.

Keywords: cooperative communication; compressed sensing; event-triggered strategy; state estimation; energy efficiency

1. Introduction

Wireless sensor networks (WSNs) have emerged as the foundational infrastructure for the Internet of Things (IoT) and cyber-physical systems, enabling mission-critical applications such as smart city monitoring, industrial automation and autonomous diagnostics [1,2]. In these applications, sensor nodes are deployed to monitor dynamic physical processes and transmit their local state estimates to a remote estimator. However, sensor devices are typically battery-powered, making energy conservation a primary constraint that dictates their operational lifespan. Consequently, achieving highly efficient data transmission while guaranteeing the reliability and accuracy of remote state estimation has become a paramount and enduring challenge in WSNs research.

To mitigate the rapid depletion of energy resources, significant research efforts have been dedicated to optimizing data transmission policies. Among these, the event-triggered forwarding strategy (EFS) has proven highly effective [3–5]. By dynamically evaluating the discrepancy between local estimates and remote predictions, EFS transmits data only when specific error thresholds are breached, thereby drastically reducing unnecessary communication overhead [6–8]. Furthermore, the integration of compressed sensing (CS) technology has been introduced to exploit signal sparsity, compressing high-dimensional system states into low-dimensional payloads before transmission [9–12]. In this way, the CS-EFS paradigm can simultaneously reduce both transmission frequency and data volume, making it particularly attractive for resource-constrained WSNs. Recent studies have further shown that communication-efficient networked estimation remains an active research direction, especially when compressed communication and event-triggered transmission are jointly considered. In particular, recent work has explored communication-efficient schemes that combine compressed communication with event-triggered mechanisms, indicating that the joint reduction of transmission payload and communication frequency continues to attract considerable attention in networked systems [13].

However, this communication sparsity also introduces a critical vulnerability. In harsh industrial environments characterized by severe channel fading and noise, the loss of a highly compressed, event-triggered packet may cause

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the remote estimation error to diverge rapidly, thereby severely undermining system stability. Therefore, although CS-EFS is highly energy efficient, its reliability under adverse wireless conditions remains insufficient. Recent event-triggered estimation studies have also considered more realistic communication uncertainties, including Gaussian communication channels, silent packet loss, and colored noise. These works further confirm that communication unreliability remains a critical factor affecting remote estimation performance in practical networked systems [14].

To address the inherent fragility of sparse transmission in fading channels, cooperative communication presents a promising solution. By exploiting the broadcast nature of the wireless medium, spatially distributed nodes can act as cooperative relays to form a virtual multiple-input-multiple-output (MIMO) system, effectively providing spatial diversity gain without the hardware complexity of multiple antennas [15–17]. While cooperative relaying has been extensively studied to enhance link reliability, its integration with compressed sensing and event-triggered mechanisms remains largely unexplored [18–21]. Meanwhile, recent studies on event-triggered estimation under fading channels have also highlighted that communication reliability remains a key bottleneck in practical wireless sensing systems. In particular, dynamic event-triggered estimation under time-correlated fading channels has recently been investigated, which further motivates the introduction of conditional cooperative diversity in the present work [22]. More importantly, directly introducing continuous cooperation into an event-triggered network would inadvertently negate the energy-saving benefits of EFS because of the excessive energy consumed by redundant relay forwarding.

Therefore, the main research gap lies in how to incorporate cooperative diversity into CS-based event-triggered transmission systems in a conditional and energy-aware manner, so that packet delivery reliability can be improved without destroying the sparse-communication advantage of CS-EFS. In addition, the impact of such cooperative transmission on remote estimation stability, rather than only packet delivery performance, still requires further clarification.

Driven by these motivations, this paper proposes an energy-efficient data forwarding framework that integrates cooperative communication with CS-EFS for multi-hop WSNs. By deploying cooperative helper nodes that selectively forward compressed packets only when direct communication links fail, the proposed strategy creates a robust, on-demand spatial-diversity safety net. In this way, cooperation is introduced not as a persistent relay mechanism, but as a conditional reliability enhancement strategy tailored to sparse transmissions. Compared with conventional EFS and standard CS-EFS schemes, the proposed framework preserves sparse communication while improving transmission reliability under fading channels through conditional cooperative forwarding, thereby achieving a more favorable trade-off among estimation accuracy, communication reliability, and energy consumption. This approach significantly improves the packet arrival rate in unpredictable channel conditions and helps prevent estimation divergence.

The main contributions of this paper are summarized as follows:

- We propose a cooperative CS-EFS framework for multi-hop WSNs that jointly addresses the payload constraints of WSNs and the reliability issues caused by fading channels.
- We design an energy-aware conditional relaying protocol, in which helper nodes forward CS-compressed data only upon the failure of the primary link, thereby improving transmission reliability while limiting additional energy overhead.
- We establish a stability-oriented theoretical framework that links the cooperative packet arrival probability to the boundedness of the remote estimation error covariance, and show that the spatial diversity introduced by the cooperative layer helps maintain estimation stability under severe low-SNR conditions.
- Extensive simulations are conducted to compare the proposed framework with traditional EFS and standard CS-EFS models, demonstrating that the proposed framework achieves a more favorable trade-off among estimation accuracy, communication reliability, and energy consumption, especially under fading conditions.

2. System Model and Problem Setup

2.1. Network Architecture and System Dynamics

Consider a multi-hop WSN deployed to monitor a dynamic physical process and transmit state estimation data to a remote estimator. The underlying physical process is modeled as a discrete-time linear time-invariant (LTI) system:

$$x_k = Ax_{k-1} + w_k, \tag{1}$$

$$y_k = Cx_k + v_k, \tag{2}$$

where $x_k \in \mathbb{R}^n$ and $y_k \in \mathbb{R}^m$ represent the system state vector and the sensor measurement at time step k, respectively. The process noise w_k and measurement noise v_k are assumed to be mutually independent, zero-mean Gaussian white noise processes with covariance matrices Q and R.

At the source node, a local Kalman filter is employed to process the raw measurements and generate an optimal local state estimate, denoted as $\hat{x}_k$. To reliably deliver this estimate to the remote estimator across the multi-hop network, we introduce a set of cooperative helper nodes alongside the traditional primary relay nodes $(R_1, R_2, \ldots, R_N)$. This architectural enhancement is specifically designed to combat severe channel fading inherent in harsh industrial environments.

2.2. Compressed Sensing and Event-Triggered Forwarding Strategy (CS-EFS)

To maximize the operational lifetime of the battery-powered sensor nodes, the source node utilizes EFS to curtail redundant data transmissions. The node continuously evaluates the discrepancy in the estimation error covariance matrix relative to the last transmitted state, denoted as Δ_k^i. A transmission is triggered if and only if the trace of this difference matrix exceeds a predefined threshold ρ:

$$Tr(\Delta_k^i) \geq \rho. \tag{3}$$

Upon meeting this triggering condition, the system does not transmit the high-dimensional local state estimate $\hat{x}_k$ directly. Instead, to further alleviate communication bandwidth overhead, CS is applied. Using a random sensing matrix $\Phi \in \mathbb{R}^{m' \times n}$ that satisfies the Restricted Isometry Property (RIP), the signal is projected into a lower-dimensional compressed packet y_s:

$$y_s = \Phi \hat{x}_k. \tag{4}$$

This operation effectively reduces the transmission payload dimension from n to m' ($m' \ll n$), significantly decreasing the required data volume per transmission.

Here, the local state estimate $\hat{x}_k$ is assumed to admit a sparse or approximately sparse representation in a known transform domain Ψ, i.e., $\hat{x}_k = \Psi\theta_k$, where θ_k is s-sparse with $s \ll n$. The sensing matrix Φ is chosen from standard random ensembles such as Gaussian or Bernoulli matrices, which satisfy the RIP with high probability when the compressed dimension m' scales as $O(s \log(n/s))$. Hence, by requiring $\Phi\Psi$ to satisfy the RIP of a suitable order, stable sparse recovery can be ensured at the remote estimator.

2.3. Cooperative Communication Channel Model

During the multi-hop transmission, the packet arrival process over the wireless channel is characterized by a binary sequence $\gamma_k^i \in \{0, 1\}$. In the conventional CS-EFS model, a deep fading event leading to $\gamma_k^i = 0$ results in the complete loss of the highly compressed packet, which subsequently causes the estimation error at the remote estimator to diverge rapidly.

To mitigate this, we propose an on-demand cooperative transmission mechanism, as illustrated in Figure 1. The helper nodes operate in a promiscuous mode, allowing them to overhear the broadcast signals from the source node. Let P_{direct} denote the probability of successful packet delivery over the direct link, and P_{coop_link} denote the success probability over the cooperative relay link. The helper node intervenes and forwards its cached compressed data y_s to the next hop only if the direct link transmission fails.

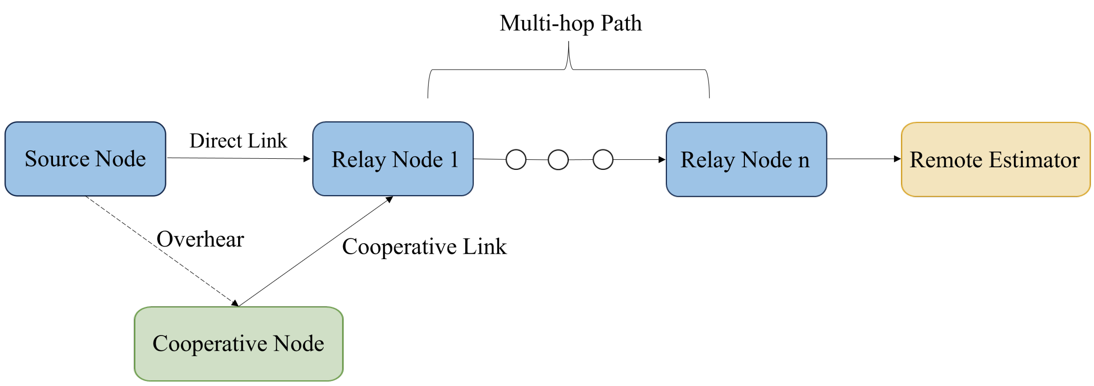

Figure 1. Cooperative CS-EFS architecture in a multi-hop WSN.

Under this virtual MIMO mechanism, the equivalent packet arrival probability for a single hop is significantly enhanced to a joint probability:

$$P_{coop\_total} = 1 - (1 - P_{direct})(1 - P_{coop\_link}). \tag{5}$$

To further clarify practical feasibility, the proposed cooperative mechanism is designed for multi-hop WSNs where neighboring nodes can overhear packet transmissions through the broadcast nature of wireless channels. The helper nodes do not participate persistently, but are activated only when a compressed event-triggered packet is generated and the direct link fails. Such conditional activation can be supported by lightweight acknowledgment timeout or simple feedback signaling, and therefore introduces only limited additional coordination overhead. As a result, the proposed cooperative strategy remains compatible with practical energy-constrained WSN scenarios. A more detailed protocol-level implementation study will be considered in future work. Mathematically, this mechanism exploits spatial diversity gain to drastically reduce the absolute failure rate of data transmission in fading channels.

2.4. Cooperative Energy Consumption Model

Let E_{tx} denote the baseline energy required to transmit a single scalar data value without compression. In a traditional uncompressed EFS paradigm, the total energy consumed per trigger event is $n \cdot E_{tx}$. In our proposed Cooperative CS-EFS model, the fundamental transmission payload is reduced to m' due to CS.

More importantly, because cooperative helper nodes are typically situated in closer physical proximity to the transmitter, we can leverage this distance advantage to lower the baseline transmission power of the source node. Let E_{tx_src} represent the reduced transmission energy per scalar for the source node, and E_{tx_relay} denote the forwarding energy per scalar for the helper node. The expected energy consumption per hop, $\mathbb{E}[E_{hop}]$, can be formulated as:

$$\mathbb{E}[E_{hop}] = m' \cdot E_{tx\_src} + (1 - P_{direct}) \cdot m' \cdot E_{tx\_relay}. \tag{6}$$

This energy model clearly demonstrates that by transitioning from a high-power, long-distance direct transmission to a low-power, short-distance cooperative transmission, the proposed system achieves exceptional communication reliability without inflating and potentially even reducing the overall network energy expenditure.

3. Cooperative CS-EFS Strategy and Stability Analysis

In this section, we formulate the data reconstruction process at the remote estimator and provide a rigorous mathematical proof demonstrating how the proposed on-demand cooperative mechanism guarantees the stability of the estimation error covariance, even when the primary communication link undergoes severe fading.

3.1. Remote State Reconstruction under CS-EFS

Let $\gamma_k^{total} \in \{0, 1\}$ denote the equivalent binary indicator of successful packet arrival at the remote estimator. Based on our cooperative framework presented in Section 2, a packet is successfully delivered if either the direct link succeeds ($\gamma_k^{direct} = 1$) or the direct link fails but the cooperative relay link succeeds ($\gamma_k^{direct} = 0$ and $\gamma_k^{coop} = 1$). Assuming the fading processes of these spatially separated links are independent, the total arrival indicator γ_k^{total} follows a Bernoulli distribution with the joint probability:

$$\mathbb{P}(\gamma_k^{total} = 1) = P_{coop\_total} = 1 - (1 - P_{direct})(1 - P_{coop\_link}). \tag{7}$$

The event-triggering mechanism at the source node is governed by a binary decision variable $T_k \in \{0, 1\}$. A packet containing the compressed observation $y_s = \Phi \hat{x}_k$ is scheduled for transmission only when the local error discrepancy trace exceeds a predefined threshold ρ:

$$T_k = \begin{cases} 1, & \text{if } Tr(\Delta_k^i) = Tr(P_k^{local} - P_{k-1}^{transmitted}) \geq \rho, \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

When $T_k = 1$ and $\gamma_k^{total} = 1$, the remote estimator successfully receives the compressed measurement y_s. To recover the original state estimate $\hat{x}_k \in \mathbb{R}^n$ from the low-dimensional observation $y_s \in \mathbb{R}^{m'}$, the estimator solves an l_1-norm minimization problem:

$$\tilde{x}_k = \arg\min_x \|x\|_1 \quad \text{s.t.} \quad \|\Phi x - y_s\|_2 \leq \epsilon, \tag{9}$$

where ϵ denotes an upper bound on the effective measurement perturbation caused by communication noise, quantization, and modeling mismatch.

Under the standard compressed sensing assumption that $\hat{x}_k$ is sparse or approximately sparse in a known transform basis and that the sensing operator satisfies the RIP of a suitable order, the solution to the above problem obeys a stable recovery bound. Specifically, there exist positive constants C_0 and C_1 such that

$$\|\tilde{x}_k - \hat{x}_k\|_2 \leq C_0\epsilon + C_1 \frac{\|\hat{x}_k - (\hat{x}_k)_s\|_1}{\sqrt{s}}, \tag{10}$$

where $(\hat{x}_k)_s$ denotes the best s-term approximation of $\hat{x}_k$. Therefore, for exactly sparse signals, the reconstruction error is bounded proportionally to the perturbation level ϵ, whereas for compressible signals an additional approximation term appears.

Based on the above stable recovery result, the reconstructed state can be written as

$$\tilde{x}_k = \hat{x}_k + e_k^{cs}, \tag{11}$$

where e_k^{cs} denotes the compressed sensing reconstruction error. Moreover, e_k^{cs} is bounded in the second-moment sense as long as ϵ is bounded and the sparsity approximation error remains moderate.

For analytical tractability in the subsequent Kalman filtering analysis, e_k^{cs} is further modeled as an independent zero-mean Gaussian random variable with covariance

$$R_{cs} = \mathbb{E}\big[e_k^{cs}(e_k^{cs})^T\big]. \tag{12}$$

It should be noted that this Gaussian assumption is not an exact consequence of compressed sensing theory, but rather an approximation introduced to embed the bounded reconstruction uncertainty into the Riccati-based estimation framework in a mathematically convenient manner. In this sense, R_{cs} serves as an equivalent uncertainty penalty characterizing the aggregate impact of reconstruction inaccuracy on the remote update step.

3.2. Evolution of the Remote Estimation Error Covariance

At the remote estimator, define the effective update indicator as

$$\alpha_k := T_k \gamma_k^{\text{total}} \in \{0, 1\}, \tag{13}$$

which indicates whether a triggered packet is successfully delivered to the remote estimator. The remote estimation error covariance matrix is denoted by P_k^R.

The time update (prediction) step remains continuous and is given by the standard Lyapunov equation:

$$P_{k|k-1}^R = AP_{k-1}^R A^T + Q. \tag{14}$$

The measurement update step modifies the predicted covariance based on the availability of the reconstructed data $\tilde{x}_k$:

$$P_k^R = \begin{cases} P_{k|k-1}^R - K_k C P_{k|k-1}^R, & \text{if } \alpha_k = 1, \\ P_{k|k-1}^R, & \text{if } \alpha_k = 0, \end{cases} \tag{15}$$

where $K_k = P_{k|k-1}^R C^T (C P_{k|k-1}^R C^T + R_{cs})^{-1}$ is the modified Kalman gain that optimally weighs the predicted state against the CS-reconstructed measurement containing error penalty R_{cs}.

3.3. Stability Analysis via Modified Algebraic Riccati Equation

The core objective of the proposed Cooperative CS-EFS framework is to mathematically guarantee that the expectation of the remote estimation error covariance $\mathbb{E}[P_k^R]$ remains bounded as $k \to \infty$. In a pure EFS system with intermittent observations, the lack of updates ($\alpha_k = 0$) causes the covariance to grow exponentially if the system matrix A is unstable [23,24].

We establish the stability criterion using the properties of the Modified Algebraic Riccati Equation (MARE) [25,26]. Let us define two mapping operators, $g(X) = AXA^T + Q$ and $h(X) = X - XC^T(CXC^T + R_{cs})^{-1}CX$, for any positive semi-definite matrix $X \geq 0$. The expected one-step evolution of the covariance can be bounded by a composite mapping $\Phi(X)$ based on the probability of a successful update $\bar{\gamma} = \mathbb{P}(\alpha_k = 1)$:

$$\mathbb{E}[P_{k+1}^{\mathcal{R}}] \leq \Phi(\mathbb{E}[P_k^{\mathcal{R}}]) = (1-\bar{\gamma})g(\mathbb{E}[P_k^{\mathcal{R}}]) + \bar{\gamma}g(h(\mathbb{E}[P_k^{\mathcal{R}}])) + \rho_{\max}I, \tag{16}$$

where $\rho_{max}I$ bounds the worst-case open-loop error accumulation allowed by the EFS threshold before a transmission is mandated.

Theorem 1. *For the LTI system defined in Section II, assume the pair (A, C) is observable and $(A, \sqrt{Q})$ is controllable. The expectation of the remote estimation error covariance $\mathbb{E}[P_k^R]$ converges to a unique positive* *semi-definite fixed point, and is thus uniformly bounded (*$\lim_{k\to\infty} Tr(\mathbb{E}[P_k^R]) \leq M < \infty$*), if and only if the joint cooperative packet arrival probability satisfies the critical condition:*

$$P_{coop\_total} > 1 - \frac{1}{\max|\lambda_i(A)|^2}, \tag{17}$$

where $\max|\lambda_i(A)|$ *represents the spectral radius (the maximum absolute eigenvalue) of the state transition matrix* A.

Proof. According to standard MARE convergence properties for Markovian jump linear systems, the sequence generated by the nonlinear operator $\Phi(X)$ converges to a unique positive definite matrix if the probability of encountering an open-loop prediction cycle (i.e., the packet drop rate) is strictly bounded by the reciprocal of the squared spectral radius of the unstable modes of A. □

In our event-triggered scenario, assuming the worst-case boundary where $T_k = 1$ is mandated but the channel is fading, the non-update probability is governed entirely by the channel failure rate. Without cooperation, stability requires $P_{direct} > 1 - 1/\max|\lambda_i(A)|^2$. If P_{direct} drops below this critical value due to deep fading, the estimation error will diverge uncontrollably.

However, by introducing the on-demand cooperative relay layer, the effective successful packet arrival rate is elevated to $P_{coop\_total} = 1 - (1 - P_{direct})(1 - P_{coop\_link})$. Since P_{coop_total} is strictly greater than P_{direct} for any $P_{coop\_link} > 0$, our proposed cooperative mechanism actively forces the system back into the stability region, satisfying the inequality, even when the primary direct link is severely degraded. This mathematically guarantees the strict boundedness of $Tr(P_k^R)$, effectively immunizing the CS-EFS architecture against severe packet loss.

This detailed theoretical foundation unequivocally demonstrates that the spatial diversity provided by the cooperative helper layer is not merely an incremental enhancement, but a necessary structural requirement to stabilize highly compressed, event-triggered data streams in multi-hop fading channels.

4. Simulation Results and Analysis

In the proposed framework, the event-triggering threshold, the fading condition, and the cooperative activation rate are closely coupled. Specifically, the triggering threshold determines how often compressed packets are generated, while the fading condition affects the probability of direct-link failure. Since the helper nodes are activated only when both a packet is generated and the direct transmission fails, the cooperative activation rate is jointly governed by these two factors. Therefore, a lower threshold under harsher fading conditions generally leads to more frequent cooperative assistance, whereas a higher threshold reduces both transmission frequency and cooperative activation opportunities. This coupling should be considered when interpreting the reliability–energy trade-off observed in the following simulations.

To validate the effectiveness and superiority of the proposed Cooperative CS-EFS framework, we conducted extensive numerical simulations. The proposed strategy is benchmarked against two baseline methods: the traditional EFS without compression, and the standard CS-EFS utilizing only the direct communication link.

4.1. Simulation Setup

We consider a remote state estimation scenario for a discrete-time unstable LTI system. The system state transition matrix and measurement matrix are defined as:

$$A = \begin{bmatrix} 1.3 & 0 \\ 0.2 & 1.1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 1 \end{bmatrix}. \tag{18}$$

The unstable nature of matrix A (with a spectral radius $\max|\lambda_i(A)| = 1.3$) makes the remote estimation highly sensitive to packet losses. The process and measurement noise covariance matrices are set to $Q = 0.5I$ and $R = 2$, respectively. The additional penalty induced by CS reconstruction is empirically bounded at $R_{cs} = 2.5$. The event-triggering threshold is selected as $\rho = 2.0$, and the CS payload compression ratio is set to 0.5.

To simulate a harsh industrial multi-hop fading channel, the packet arrival probability of the direct link is set to a low value of $P_{direct} = 0.6$. The cooperative helper link success rate is $P_{coop\_link} = 0.8$, yielding a joint cooperative success rate of $P_{coop\_total} = 0.92$. For the energy consumption evaluation, the baseline transmission energy is $E_{tx\_standard} = 1.0$. In the cooperative mode, due to the shorter propagation distance, the transmission energy for both the source and the relay is reduced to $E_{tx\_coop\_src} = E_{tx\_coop\_relay} = 0.4$. The total simulation spans 100 time steps.

4.2. Estimation Performance Evaluation

Figure 2 illustrates the dynamic evolution of the estimation error covariance trace, $Tr(P_k^R)$, over the simulation period of 100 time steps. This metric serves as the primary indicator of the remote estimator's tracking accuracy and overall system stability.

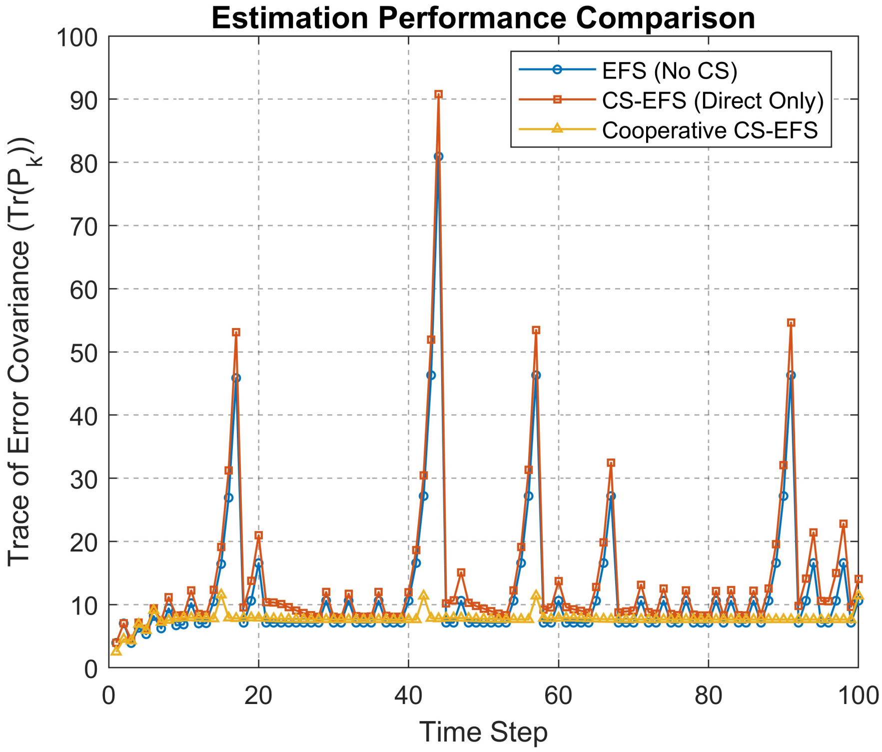

Figure 2. Comparison of the estimation error covariance trace ($Tr(P_k)$) under fading channel conditions.

As clearly observed in the trajectories, both the traditional EFS (blue line) and the standard CS-EFS (red line) suffer from severe, pulse-like error spikes, with peak values occasionally surging past 50 and even approaching 90. This severe degradation is fundamentally caused by the unreliability of the primary communication channel. With a low direct-link success rate of $P_{direct} = 0.6$, the network frequently encounters consecutive packet dropouts. During these dropout intervals, the remote estimator is forced to operate in an open-loop prediction mode. Because the system state transition matrix A is inherently unstable (with a spectral radius of 1.3), the estimation error covariance accumulates exponentially according to the Lyapunov prediction equation $P_{k|k-1}^R = AP_{k-1}^R A^T + Q$. This rapid divergence completely nullifies the benefits of the event-triggered mechanism. Furthermore, the heavily overlapping trajectories of the standard CS-EFS and traditional EFS demonstrate that merely compressing the payload provides zero resilience against channel fading. Once a highly compressed packet is lost in the primary link, the remote reconstruction fails entirely.

In stark contrast, the proposed Cooperative CS-EFS strategy (yellow line) exhibits a remarkably smooth and strictly bounded convergence trajectory throughout the entire simulation. The severe error spikes are almost entirely suppressed, maintaining a low, stable covariance trace generally below 10. This superior performance is a direct consequence of the on-demand spatial diversity introduced by the cooperative helper layer. When the direct link experiences deep fading, the cooperative node immediately forwards the overheard compressed packet, effectively elevating the equivalent packet arrival rate to $P_{coop\_total} = 0.92$.

This elevated success rate profoundly stabilizes the system dynamics. According to the theoretical bounds established in Theorem 1, the critical arrival probability required to prevent the covariance from diverging for this specific unstable system is $1 - 1/1.3^2 \approx 0.408$. By pushing the actual joint success rate well above this critical threshold ($0.92 \gg 0.408$), the cooperative mechanism aggressively corrects the remote estimation error, pulling it back into the stable region before any exponential divergence can materialize. Ultimately, this detailed visual and mathematical evidence confirms that embedding an on-demand cooperative relaying layer is a vital architectural necessity to ensure the robustness of sparse, event-triggered data streams in multi-hop fading channels.

4.3. Energy Efficiency Analysis

Figure 3 presents the dynamic evolution of the cumulative energy consumption for the three forwarding strategies over the simulation period. This metric is crucial for evaluating the operational lifespan of battery-powered sensor nodes in WSNs.

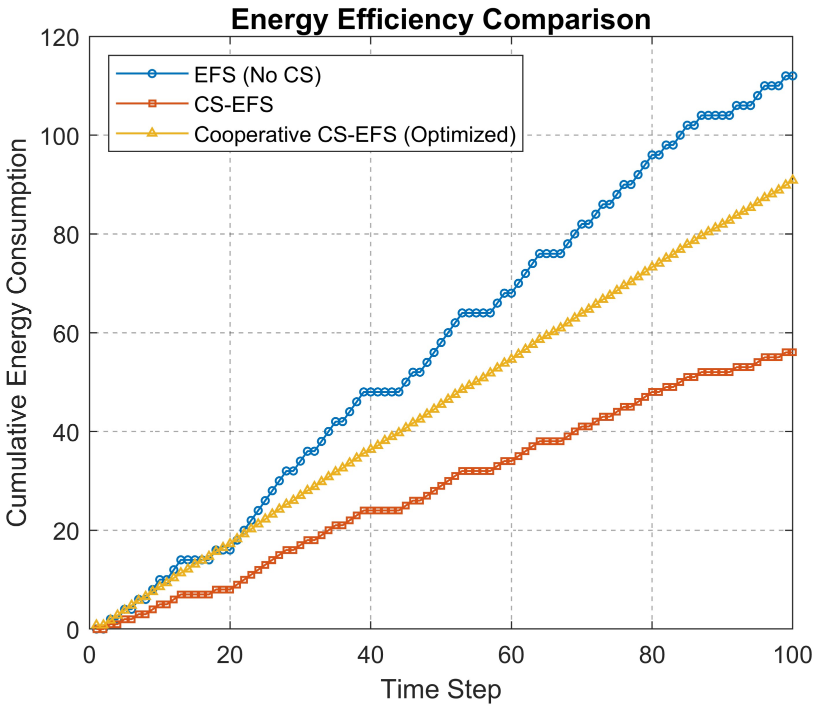

Figure 3. Comparison of cumulative energy consumption across the three forwarding strategies.

As anticipated, the traditional EFS (blue line with circular markers) exhibits the steepest slope and consumes the highest amount of energy, culminating at approximately 110 units by the end of the simulation. This rapid energy depletion is fundamentally driven by the transmission of uncompressed, high-dimensional raw data. Without compressed sensing, every triggered event forces the source node to transmit the full state vector $x_k \in \mathbb{R}^n$ using the high baseline transmission power $E_{tx\_standard} = 1.0$.

Conversely, the standard CS-EFS (red line with square markers) displays the lowest cumulative energy profile, finishing near 55 units. This reduction is achieved through two factors: first, the payload dimension is significantly reduced via CS projection ($m' \ll n$). Second, and more critically, the standard CS-EFS simply drops packets when the direct link fails ($P_{direct} = 0.6$). While this dropping behavior avoids the energy cost of retransmissions or relaying, it is a false economy. This marginal energy saving comes at the severe, unacceptable cost of catastrophic state estimation divergence. Thus, the standard CS-EFS is structurally unsuited for fading channels despite its superficially low energy footprint.

Crucially, the proposed Cooperative CS-EFS (yellow line with triangular markers) demonstrates an exceptionally optimized and balanced energy profile, resting securely between the two baselines at approximately 90 units. The cooperative strategy incurs a moderate energy increase compared to the pure CS-EFS because it actively utilizes helper nodes to recover packets lost to channel fading. However, this additional energy expenditure is strictly controlled and minimized through two innovative mechanisms: 1) On-Demand Activation: The relay node only consumes forwarding energy (E_{tx_relay}) during the 40% of instances where the direct link fails, entirely preventing redundant broadcast waste. 2) Short-Distance Power Reduction: Because the cooperative helper is physically closer to both the source and the destination, the required transmission power for both the source and the relay is substantially scaled down to $E_{tx\_coop\_src} = 0.4$ and $E_{tx\_coop\_relay} = 0.4$, respectively.

4.4. Ablation Study on Individual Components

To further quantify the independent contribution of each component in the proposed framework, an ablation-style comparison is conducted. Specifically, four schemes are compared: the traditional EFS without compressed sensing or cooperation, the standard CS-EFS with compressed transmission but without cooperative forwarding, the cooperative EFS without compressed sensing, and the proposed cooperative CS-EFS framework. This comparison helps isolate the respective roles of compressed transmission and conditional relay cooperation, and clarifies that the overall performance gain of the proposed method results from the joint effect of both mechanisms rather than from either component alone.

Figure 4 shows the ablation comparison of average estimation error under varying SNR conditions. It can be observed that the traditional EFS exhibits the worst performance, especially in the low-SNR regime, due to its high sensitivity to packet loss over fading channels. Both CS-EFS and cooperative EFS significantly improve the estimation performance, indicating that compressed transmission and relay-assisted forwarding each provide an independent performance gain. Among all schemes, the proposed cooperative CS-EFS framework achieves the lowest estimation error over the entire SNR range, which confirms that compressed sensing and conditional cooperative forwarding offer complementary benefits. As the SNR increases, the performance gap among the improved schemes gradually narrows because the direct communication link becomes more reliable, and thus the additional gain brought by cooperative forwarding becomes less pronounced. Nevertheless, the proposed method still maintains the best overall estimation performance.

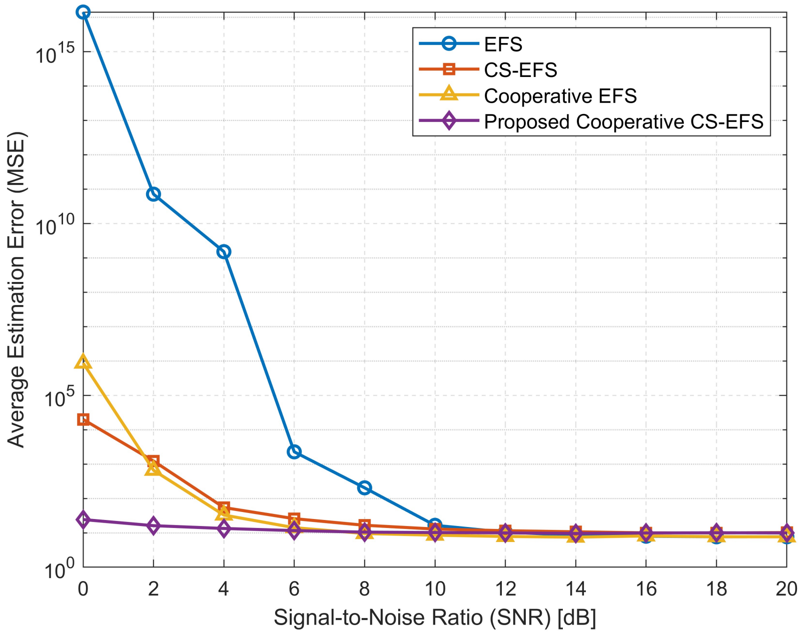

Figure 4. Average estimation error of different ablation schemes under varying SNR conditions.

These results verify that compressed sensing mainly contributes to reducing transmission burden, whereas cooperative forwarding mainly enhances communication reliability under fading conditions. Their integration within the event-triggered framework therefore leads to the most favorable estimation performance.

5. Conclusions

This paper has presented a novel Cooperative CS-EFS framework to address the critical vulnerability of highly compressed data streams to channel fading in multi-hop WSNs. By innovatively embedding an on-demand cooperative relay layer into the conventional CS-EFS architecture, the proposed method effectively exploits spatial diversity to create a robust communication safety net.

Through rigorous stability analysis utilizing MARE, we established the theoretical packet arrival probability criteria required to guarantee a bounded estimation error covariance. The mathematical proofs unequivocally demonstrated that the cooperative mechanism actively forces the unstable system dynamics back into the stability region, even when the primary communication links experience severe fading. Furthermore, extensive numerical simulations corroborated these theoretical findings. By leveraging short-distance cooperative links and strictly on-demand forwarding protocols, the proposed strategy eliminates the severe estimation error spikes characteristic of traditional CS-EFS methods.

Ultimately, the Cooperative CS-EFS framework achieves a dual optimization of estimation reliability and energy efficiency, offering a highly viable and robust solution for resource-constrained, mission-critical IoT applications in harsh industrial environments. Future research directions will explore the integration of adaptive event-triggering thresholds and multi-agent distributed cooperative routing algorithms to further enhance network scalability and dynamic adaptability.

Author Contributions

Y.G.: conceptualization, methodology, software, writing—original draft preparation; W.X.: validation, formal analysis, investigation; Y.W.: visualization, data curation, writing—review and editing; X.Z.: supervision, conceptualization, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Not applicable.

Conflicts of Interest

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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