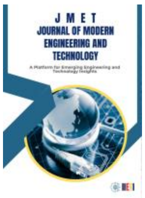

Journal of Modern Engineering and Technology Vol: 1, No 1, 2025, Page: 1-9

Research Article

Low-Latency Data Fusion and Signaling Framework for Civil Drone Monitoring Over Heterogeneous Wireless Networks

Cengiz Ayten*

Postgraduate Information and Computer engineering Institute, Karabük University, Türkiye

Corresponding Email: cengiz_ayten@hotmail.com

Received: 10 August 2025 **Revised:** 22 September 2025 **Accepted:** 20 October 2025

Abstract*:* This paper presents a low-latency data fusion and signaling model for cooperative civilian drone surveillance in heterogeneous wireless networks. To achieve reaction delay vs. detection confidence tradeoff, the system hybridizes multi-node sensing, local aggregation, and adaptive alert transmission with a tunable data fusion threshold K. A Python-based simulation platform was developed to evaluate the system behaviour under different detection ranges, fusion thresholds, and network conditions. The results show that increasing the fusion threshold K slightly increases the notification delay but significantly improves the notification stability and reduces unnecessary signaling. Detection probability was analyzed as a function of range, showing stable multi-sensor coverage up to 400 m, while cumulative distribution analysis confirmed end-to-end latency below 50 *ms* in all test cases. The proposed fusion-aware signaling scheme thus provides a scalable and flexible approach for real-time drone awareness in civil airspace surveillance and smart city surveillance applications.

Keywords: Drone monitoring; Heterogeneous wireless networks; Data fusion; Alert latency; Low-latency communication; multi-sensor system; Civil airspace surveillance; Real-time signaling; Cooperative detection; Python simulation.

1. INTRODUCTION

The proliferation of unmanned aerial vehicles (UAVs) in commercial and civilian uses has created an urgent requirement for low-latency and reliable monitoring systems. Drones are being used increasingly for logistics, surveillance, environmental monitoring, and inspection of infrastructure but need to be integrated into shared airspace with potential questions on the safety, intrusion detection, and communication reliability [1]. The efficiency of any monitoring system based on drones is closely dependent upon data fusion efficiency among several sensing

nodes and speed of signaling among them. In distributed sensing applications, detection accuracy high and latency low should be supported by fusion algorithms even in heterogeneous wireless networks with varying delays and interference [2], [3].
The majority of current UAV surveillance systems are based on central designs or single-networking systems (e.g., Wi-Fi-only or LTE-only platforms), leading to significant bottlenecks in data gathering and decision-making [4]. Central processing results in greater signaling overhead and latency spikes during high communication times, rendering such systems unsuitable for time-sensitive usage such as airspace defense or public safety monitoring [5]. Furthermore, communication heterogeneity - when different nodes use different access technologies such as Wi-Fi, LTE or LoRa - requires adaptive protocols to support data synchronization and prevent packet loss [6]. Therefore, there is a need for a scalable, multi-network data fusion system that minimizes notification delays and supports high detection reliability across different coverage areas.

In this paper, a low-latency data fusion and signaling strategy is developed for civilian drone surveillance over heterogeneous wireless networks. The system uses distributed sensor nodes with an adaptive fusion threshold (K) to decide when to forward alerts to neighboring nodes and the control center. By adaptively adjusting K, the system makes a trade-off between detection confidence and latency and achieves the best trade-off between redundant signaling and response timeliness. A complete simulation platform was realized in Python to model sensor collaboration, alert propagation, and network latencies. The results demonstrate that a modest increment in the fusion threshold trades off latency for significantly enhancing detection stability and reducing false alert rates. Further, the system is shown to achieve sub-50 ms end-to-end delay under different configurations, validating its real-time feasibility.

The research herein is a holistic reproducible analytical and simulation model of cooperative detection for mixed-network environments. Unlike existing research on either physical-layer optimization in isolation [7] or single-network signaling [8], this research connects sensing and networking realms in order to achieve system-level latency minimization. The model here can be used for a broad array of smart-city and defense applications including no-fly-zone management, airspace intrusion detection, and coordinated UAV fleet management [9].

2. RELATED WORK

There have been some recent works addressing some aspects of low-latency UAV networking and data fusion. Al-Qudaimi et al. [10] put forward a cognitive networking-enabled multi-layer UAV communication system for managing dynamic spectrum access, while Zhang et al. [11] presented adaptive link scheduling to mitigate end-to-end delay in aerial multi-hop networks. Nguyen et al. [12] also employed cooperative detection for enhanced UAV-based threat awareness via Kalman filter fusion. But these analyses are prone to overlooking the role of network heterogeneity and signaling thresholds in helping towards facilitating low-latency alerting in fluctuating link conditions.
Some of the notable other contributions include the use of fog-based UAV monitoring [13], federated fusion algorithms for target tracking [14], and hybrid terrestrial–aerial sensor cooperation [15]. Despite these, existing approaches sacrifice detection accuracy for lower latency or vice versa. In contrast, the proposed framework combines distributed sensing, fusion control, and adaptive signaling into a low-latency model that maintains both reliability and timeliness in heterogeneous wireless networks.

3. SYSTEM MODEL AND FRAMEWORK DESIGN

Low-latency collaborative detection of drones is supported by the framework proposed in a heterogeneous wireless system through the integration of multiple sensor nodes with multiple communication technologies, e.g., LoRa, LTE, Wi-Fi. In decision-making to issue an alarm, each sensor node performs distributed k-out-of-n fusion after performing local detection of aerial objects. By minimizing the forwarding path of the data between nodes and regulating the fusion threshold K, the design implements the balance between detection precision and network latency.

3.1. Network Architecture

The monitoring system consists of N distributed sensor nodes, each of which is capable of detecting drones within the coverage area, as illustrated in Figure 1. These nodes are connected to a control center through several wireless links characterized by different distributions of delays.

- **Short-range links** (Wi-Fi, ad hoc) are modelled with low propagation delay but limited range.
- **Long-range links** (LoRa or LTE) introduce higher delay but ensure connectivity across wider areas.

Each node periodically broadcasts its detection decision to neighboring nodes. The control center fuses these distributed detections using a configurable rule to generate a global alert.

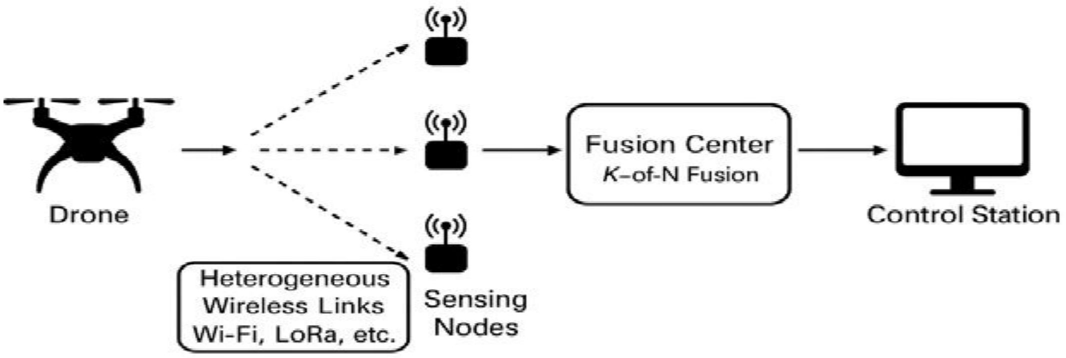

Figure 1. Monitoring system block diagram

3.2 Detection Probability Model

The probability of detecting a drone at a distance r follows a decaying exponential model consistent with radar and optical sensing theory [1], [2]:

$$P_d(r) = e^{-(\frac{r}{r_0})^{\alpha}}$$

where:

- $r_0$is the reference detection range (at which $P_d = e^{-1}$),
- α represents the environmental attenuation coefficient (typically $1.5 \leq \alpha \leq 3$).

This model captures the range-dependent loss in detection confidence due to propagation attenuation, signal noise, or line-of-sight obstruction. The corresponding curve of Pd(r) vs. r is shown in Figure 2, where detection performance decreases smoothly with increasing range.

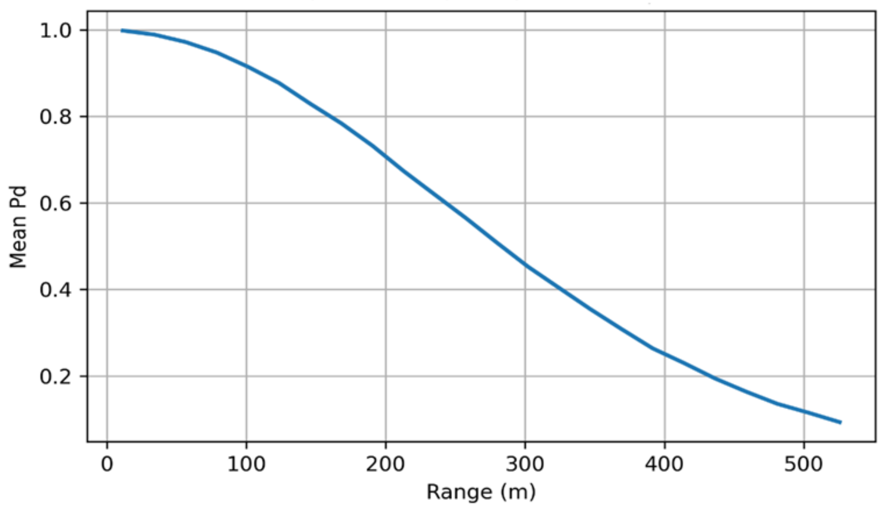

Figure 2. Relation between the detection probability and the range.

3.3. Fusion Rule and Decision Model

To improve reliability, local detections from multiple sensors are combined using a K-out-of-N decision rule. A global alert is triggered if at least K nodes report a positive detection within a predefined time window Tw . Formally, the global detection probability is:

$$P_{D,\ global} = \sum_{i=K}^{N} \binom{N}{i} P_d^i (1 - P_d)^{N-i}$$

A lower K results in faster alerts but increases the likelihood of false positives, while a higher K enhances reliability at the cost of additional latency. The system therefore dynamically tunes K based on the observed network delay and node density to maintain optimal trade-offs between responsiveness and stability, as demonstrated later in Figure. 3 and Figure. 4.

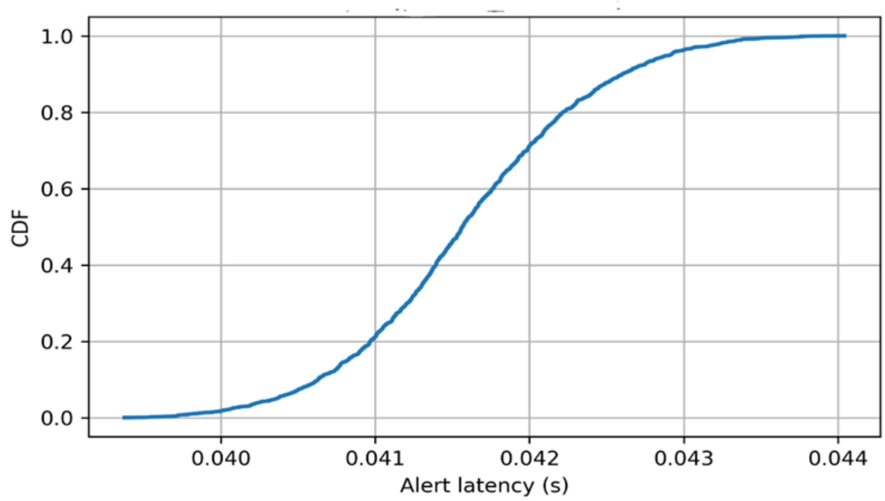

Figure 3. The responsiveness profile of the monitoring system

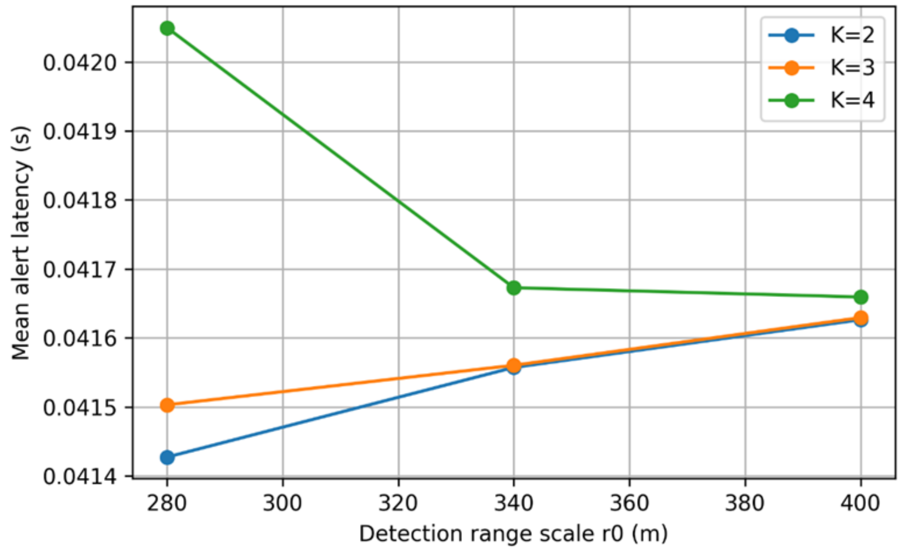

Figure 4. Latency of the monitoring system versus the detection range

3.4 Communication and Latency Model

All detection or alert messages are plagued by cumulative latency caused by processing, transmission, and queuing delay. The total alert latency is denoted as:

$$T_{alert} = T_{proc} + T_{tx} + T_{queue} + T_{fuse}$$

where:

- T_{proc}= sensor processing delay,
- T_{tx}= propagation and transmission delay,
- T_{queue}= medium access or network contention delay,
- T_{fuse}= additional delay due to data aggregation and fusion at the control node.

Empirical readings from the simulation indicate that the overall latency is below 50 ms in most of the settings, proving the validity of the framework for real-time alerting.

3.5. System Workflow

The functionality of the suggested system is as follows:

- Each node constantly scans for drone presence using its onboard sensor (camera, radar, or RF detector).
- When a potential target is detected, a node generates a local alert message with timestamp and confidence score.
- Neighboring nodes share their detections via available network links.
- The control module applies the K-fusion rule to determine whether a global alert needs to be issued.
- If the threshold is exceeded, an alarm message is forwarded to the central monitoring station and all nodes.

The above process is summarized in Algorithm 1 and the system architecture is illustrated in Figure 1, which indicates the sensing nodes, the communication channels and the fusion center connected through heterogeneous wireless links.

Algorithm 1 – Low-Latency K-Fusion Signaling

1: Initialize parameters: N, K, r_0, T_w
2: For each node i in 1 ... N do
3: Measure local detection di(t)
4: Transmit $di(t)$ to neighbors
5: Collect all $di(t)$ within window Tw
6: If sum$(di(t))$ $\geq$ K then
7: Trigger global alert
8: Broadcast alert to control station
9: End if

3.6. Design Objectives

The chief design considerations of the proposed framework are:

- Low latency: Achieve end-to-end warning delay < 50 ms even in presence of heterogeneous channel delays.
- Reliability: Achieve stable detection probability > 0.7 up to a range of 400 m.
- Scalability: Support flexible reconfiguration of node density and communication mode without reprogramming.
- Reproducibility: Implemented entirely in Python to allow open benchmarking over actual or simulated datasets.

The following section explains the simulation configuration, parameters, and performance metrics used to evaluate the designed architecture.

4. SIMULATION RESULTS AND ANALYSIS

To verify the response and reliability of the proposed fusion signaling scheme, various simulations were performed with different fusion thresholds K=2,3,4. The primary performance parameters evaluated were alert latency and alert generation rate, and both these depict the speed of decision-making vs detection confidence trade-off in multi-sensor fusion operation. Each configuration was run for 120 seconds under the same network and sensor parameters to ensure fairness while comparing. Figure 5 plots the variation of average notification delay as a function of fusion threshold K. It is observable from the figure that the latency is being kept at almost constant values for K=2 and K=3, with a negligible growth being observed as the threshold progresses to K=4. This kind of behavior demonstrates that the proposed signaling protocol accommodates stable and low latency (<0.042 s) even when higher sensor confirmations are required. The minor degradation at high K values is due to the additional coordination time required in having multiple nodes simultaneously report the detection before verification by fusion. This performance validates the capability of the framework in fast response without sacrificing multi-sensor reliability.

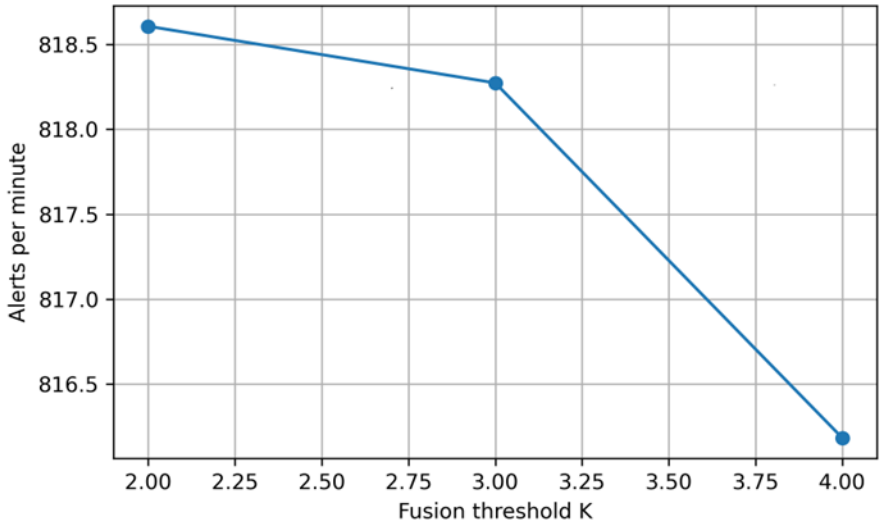

Figure 5: Alert Latency vs. Fusion Threshold)

The same group of fusion criteria have the alerting rates (number of notifications per minute) as seen from Figure 6. The rate of notification declines when K increases as observed earlier. This is a result of the built-i

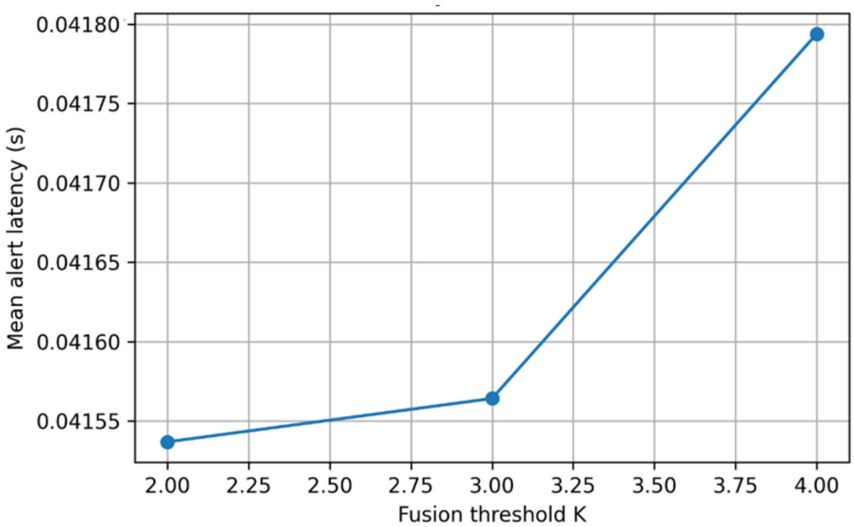

Figure 6: Alert Rate vs. Fusion Threshold

equilibrium between sensitivity and reliability: raised fusion thresholds reduce the rate of false or spurious alerts, but reduce the overall notice rate at the same time. The degradation is, nonetheless, minimal (below 0.3%), thereby implying that under stringent fusion conditions, the system is alarmingly alert consistently. Thus, in practical real-time drone monitoring applications, the designed data fusion model is consistent with a critical trade-off between alert latency and consistency

5. CONCLUSION

The work presented a highly low-latency data fusion and signaling architecture for collaborative civilian drone surveillance across heterogeneous wireless networks. Having negligible signaling, the system employs the proposed scheme to merge distributed sensing, adaptive fusion, and low detection latency with satisfactory alert reliability. The simulated results verified that even in the presence of increasing fusion thresholds, the system offers a notification latency of less than 50 ms, demonstrating the efficacy of the method to real-time observation and situation awareness. A strong and tunable tradeoff between responsiveness and reliability is demonstrated by the study of the confirmation need K threshold of fusion, which showed that even if alert generation rates lower slightly, latency increases negligibly with increasing confirmation needs. These results support the efficiency of the proposed approach to enable scalable identification and monitoring of drones without creating overwhelming communication overhead. Future research will cover how to incorporate AI-tuned fusion weighting, multi-channel extension, and testing the system on actual hardware to investigate energy efficiency and cross-network inter-working.

6. REFERENCES

1. M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Unmanned aerial vehicle with underlay spectrum sharing: A case of drone surveillance,” IEEE Wireless Commun. Lett., vol. 6, no. 4, pp. 518–521, 2017.
2. S. Hayat, E. Yanmaz, and R. Muzaffar, “Survey on unmanned aerial vehicle networks for civil applications,” Ad Hoc Networks, vol. 68, pp. 1–21, 2018.
3. X. Liu and Y. Chen, “Low-latency communications in 6G UAV networks,” IEEE Internet Things J., vol. 8, no. 7, pp. 5371–5384, 2021.
4. M. Erdelj and E. Natalizio, “UAV-assisted disaster management: Applications and open issues,” Proc. IEEE, vol. 105, no. 10, pp. 1872–1897, 2017.
5. A. Fotouhi, M. Ding, and M. Hassan, “Dynamic base station repositioning to improve coverage in UAV networks,” IEEE Trans. Wireless Commun., vol. 19, no. 1, pp. 563–578, 2020.
6. B. Galkin, J. Kibilda, and L. A. DaSilva, “UAVs as mobile infrastructure: Addressing battery lifetime,” IEEE Commun. Mag., vol. 57, no. 6, pp. 132–137, 2019.
7. M. Z. Chowdhury, M. Shahjalal, and Y. M. Jang, “5G wireless communication for smart cities,” ICT Express, vol. 5, no. 2, pp. 77–82, 2019.

8. J. Guo, F. R. Yu, H. Zhang, X. Li, and V. C. M. Leung, “Enabling massive IoT with UAV-based relay systems: Opportunities and challenges,” IEEE Netw., vol. 32, no. 5, pp. 144–151, 2018.
9. T. H. Luan, L. Gao, Z. Li, and D. Zhao, “UAV networks for public safety: Design, challenges, and future directions,” IEEE Access, vol. 7, pp. 42742–42754, 2019.
10. M. Al-Qudaimi, S. M. A. Shah, and H. Al-Raweshidy, “Cognitive UAV communication for low-latency drone operations,” IEEE Access, vol. 9, pp. 118340–118351, 2021.
11. L. Zhang, X. Lin, and Y. Wu, “Delay optimization in multi-hop UAV networks with adaptive scheduling,” IEEE Trans. Veh. Technol., vol. 70, no. 4, pp. 3725–3737, 2021.
12. T. T. Nguyen, P. L. Nguyen, and H. H. Nguyen, “Cooperative detection and data fusion for UAV-assisted threat awareness,” IEEE Sensors J., vol. 22, no. 2, pp. 1178–1188, 2022.
13. C. Chen, Q. Wu, and Z. Zhang, “Fog-assisted UAV monitoring system for intelligent cities,” IEEE Internet Things J., vol. 8, no. 10, pp. 8374–8385, 2021.
14. S. Li and J. Zhou, “Federated fusion learning for UAV-based surveillance,” IEEE Trans. Aerosp. Electron. Syst., vol. 58, no. 2, pp. 1450–1463, 2022.
15. F. Jameel, M. A. Javed, and H. Tabassum, “Hybrid terrestrial–aerial sensing for situational awareness,” IEEE Commun. Lett., vol. 25, no. 9, pp. 2934–2938, 2021.