Vol. 08, No. 2 (2026) 1203-1216, doi: 10.24874/PES08.02B.010

Proceedings on Engineering Sciences

www.pesjournal.net

OPTIMIZING DRONE SWARM-BASED WIRELESS NETWORK USING STOCHASTIC MODEL AND CONTROLLER APPROACH

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Received 18.12.2025.
Revised 18.03.2026.
Accepted 02.04.2026.

Keywords:

Wireless networked control systems, Drone swarms, Stochastic optimal control, Event-triggered communication, Multi-agent coordination, Network scheduling and control co-design

A B S T R A C T

Wireless control drone swarm systems are more and more widely preferred and be chosen for its potential to reduce the cost of communication network. Yet, the performance of such systems is largely compromised due to network inherent limitations, such as time-varying delays, packet dropouts and bandwidth constraints. The traditional control and scheduling schemes such as time-triggered communication and static bandwidth allocation are not able to provide an adaptive control under dynamic network conditions which results in inefficient control performances. This article discusses a distributed control architecture for autonomous drone swarms in presence of a Wireless Networked Control Systems (WNCS), where the wireless device underpinning some disruptive behaviors such as stochastic delays, packet loss and bandwidth availability. To this end, a joint optimization algorithm is developed, where stochastic model predictive control, event-triggered communication, and network-aware scheduling are integrated into a control framework. There is a decentralized local control for each agent using formation consensus-based control rules for tracking. The approach is adaptive to communication noise with quantized value estimation and decentralized triggering. Numerical simulations of the developed approach are developed in MATLAB which span over three case studies: (1) baseline Linear Quadratic Regulator (LQR) control in presence of packet loss and delay, (2) online model predictive control in the presence of uncertain dynamics and adaptive scheduling and (3) formation flying with swarming drones with consensus. The experiments show that the proposed method is robust, scalable, and bandwidth efficient. Average tracking and state errors are limited and communication loads are suppressed by event-triggered updates. Furthermore, robustness is demonstrated against the challenging operating environment by visualizing packet loss.

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1. INTRODUCTION

The fast development of the wireless communication and networked control system technology, has greatly improved the operational capabilities of the autonomous systems, especially the Unmanned Aerial Vehicles (UAVs). Drone swarms, which are a collaborative group of UAVs, have been one of the disruptive technologies with various potential applications such as aerial surveillance, environmental surveillance, precision agriculture, disaster management, and military use (Chen et al., 2020). Drone swarms are found to be significantly more scalable, redundant, and coverage providing, than single agent systems (Alqudsi & Makaraci, 2025). but they only work if participants can effectively perform smooth, coordinated actions amid dynamic and unpredictable conditions, which require reliable real-time communication. Each UAV in swarm operations behaves like an autonomous agent in a distributed system. The coordination requires a permanent exchange of sensor readings and command signals through common wireless communication channels (Mozaffari et al., 2019). Such interactions between a controller and a drone are traditionally treated as wireless networked control systems, where the sensor measurements are sent to the controller in a remote location, and the controller sends control commands to the drone through the same wireless network. Systems of these type are extremely sensitive to communication disturbances such as: limited bandwidth, noisy stochastic delays, packet loss, interference and signal attenuation (Schenato et al., 2007). They are more issues in large- scale swarms where contending or multiple drones for finite network resources exist (Grosjean et al., 2025). The scheduling of communication is usually decoupled from the design of control in conventional network control frameworks. However, this decoupling does not apply in swarm systems where the network dynamics and control performance directly affect each other (Lun et al., 2024). Event-based communication policies have been considered to reduce energy consumption by only transmitting data when system states deviate from their "normal" levels. Though these techniques help reduce unwanted transmissions, the advantages decrease when there is no control logic integration involved (Tabuada, 2007). A not suitable suited scheduling policy can result in nullifying the utility of the controller even if sophisticated controllers are being used. A new distributed framework for joint control and communication-based scheduling in WNCSs for drone swarm has been presented in this study. In contrast to traditional control methodologies, which are based on perfect communication networks or centralized architectures, this scheme captures the stochastic nature of wireless phenomena, such as packet drop outs, and latency as well as bandwidth constraints. Stochastic optimal control approaches with event-triggered transmission policy. Furthermore, this proposed framework can assure stability and performance of controller in a bad case network environment. The control framework is generalized to a setting with multiple agents, where each agent acts independently but does so under consensus-based formation tracking between agent in terms of local interactions and communication constraints. Since this technique could be applied to a variety of cases, simulations are presented for an increasing set of test cases in MATLAB from simple single drone control on base-line, to drone multi-formation coordination. These simulations confirm the robustness, scalability and network throughput of the proposed system. A central contribution of this work is the quantification of the relationship between reliability in transmission and power. By simulating the mapping of transmission power to packet success rate, an optimal transmission policy is got that achieves balance between robustness against communication errors and energy saving.

The remainder of the paper is structured as follows. The existing literature of drone swarm control, WNCS as well as joint communication-control codesign approaches are reviewed in Section 2. Meanwhile Section 3 presents the architecture of WNC-Drone Swarm System, to describe considering wireless communication and network affecting drone swarm. The system model is described in Section 4, which he gives the mathematical representation of the drone dynamics and communication delays and packet loss model. Section 5 discusses the algorithms of implementing the stochastic control design for a distributed drone swarm. Section 6 presents the numerical simulation with MATLAB in order to illustrate the effectiveness of the proposed control and scheduling methods over different network scenario. The discussion in Section 7 compares across different control schemes and communication configurations based on the simulation results. Section 8 concludes this paper providing emphasis on the contributions and also listing out ideas for further research of scalable and reliable WNCS-enabled swarm of drones in large scale.

2. RELATED WORKS

The rise of autonomous drone swarms has triggered significant research efforts from various aspects, among which communication and control as well as resource scheduling in WNCS are two closely correlated factors. Drone integration on Industry 4.0 systems, focusing on control decoupling, wireless communication protocols and possible swarm behaviors for cooperative task execution. Such interplay of network and control design is highly desirable for guaranteeing timeliness, scalability and stability in large-scale drone operations (Tsaramirsis et al., 2022). On a separate study, based on industrial drone applications, controller-based tracking model also corresponds to wireless control in real-time UAV systems (Al-Hamadani et al., 2025). The theoretical basis and implementation principles for networked control systems were studied in detail in (Sarangapani & Xu, 2016) that proposes a systematic

approach for modeling, stability analysis and optimal controller design under the effects of network-induced limitations such as delay and packet loss. Nevertheless, preliminary seminal research, in (Mansouri et al., 2015), emphasized centralized coordination combined with autonomy in UAV systems so drones could work independently and together towards a common goal. This has been particularly useful in military and reconnaissance operations. The study, in (Katila, 2018), continued in this direction to investigate medium access control and the routing protocol for 5G-enabled UAV networks, with a focus on multi-hop which can decrease packet collisions through achieving connectivity. The researchers, in (Zhou et al., 2018), also introduced a model for continuous patrolling in uncertain environments and suggested frameworks which apply centralized and decentralized decision-making among UAVs swarms. Similarly, the researchers in (Zeng et al., 2018) also studied the stability of drone swarms connected via cellular, developing mathematical models for control and communication integration. Reinforcement Learning (RL) has also been applied to issues of network deployment and control. For example, in (Hammami et al., 2019), the authors have used multi-agent RL for battery optimization and cooperative communication in the context of drone-assisted cellular networks. The efficient execution of tasks and the decentralization was the interest in (Viseras et al., 2019), were the study presented a beehive-based information-gathering system. The researchers, in (Wolf et al., 2019), focused on security, dealing with adversarial threats in decentralized drone swarms and a problem of rising importance in smart city applications. For distributed adaptive formation control protocols which improve connectivity and robustness in unknown environments with unpredictable dynamics (Rahmani et al., 2020).

In the context of learning-based control, the researchers, in (Venturini et al., 2021), used distributed RL for optimal and adaptable UAV swarm manoeuvres. Recently, in (Rovira-Sugranes et al., 2022), delivered an exceptional survey on AI based routing protocols stressing on the requirement for topology sensitive designs adopted for UAV mobility. The researchers, in (Mager et al., 2022), investigated the stability under bandwidth constraints by proposing scalable control mechanics for saturated wireless channel. Newer research also addresses higher level optimization and swarm shaping. The research, in (Barbeau et al., 2022), focused on collaborative drones flying in 5G and cloud-networks, concentrating on scalability and privacy issues. The researchers, in (Bansal et al., 2023), proposed a multi-objective optimization strategy for achieving swarm coordination. The researchers, in (Yoo et al., 2023), introduced RL-enabled topology control approaches for improving throughput and energy consumption. The researchers, in (Majee et al., 2024), introduced hybrid communication strategy to dynamically deal with the complexity of drone swarm communication in difficult missions. Although these contributions have greatly advanced the field, they tend to address communication protocols or control mechanisms individually. In swarm of drones, communication scheduling is very important because there are limited bandwidth and high communication requirements. The use of time-based scheduling methods that are either fixed or variable-cycle nature in traditional M2M communication systems are simple to implement, but can induce traffic jam on the network (Schenato et al., 2007). Event-driven approaches have made further improvements by transmitting information only upon important state transitions to reduce the communication load and to increase the responsiveness of control applications (Tabuada, 2007). A co-design approach (Pang et al., 2024), is proposed by which scheduling and control are jointly considered to enhance real-time performance in large-scale WNCS, mitigating packet loss while enhancing the stability of the network. In addition, adaptive mechanisms such as priority based (Ma et al., 2020), optimization based (Issariyakul & Hossain, 2005) and RL based scheduling (Fu et al., 2024), change dynamically the transmission policies according to network state or learning from interaction with the environment.

Nonetheless, most of approaches still consider control and scheduling as two distinct layers, which may not fully exploit the system behavior. From a control viewpoint, methods such as MPC (Model Predictive Control) (Bordei & Halanay, 2025), stochastic MPC (Wang et al., 2018) and delay-aware MPC (Gatsis et al., 2014) have been adopted to combat the negative impacts of delays and packet losses. However, these approaches are computationally intensive and generally not easily deployable in real-time. To deal with these issues, deep RL (e.g., DDPG, PPO, SAC) (Wang et al., 2023) and multi-agent reinforcement learning are employed to learn robust policies for distributed systems in the presence of uncertain networking dynamics. Cross-layer co- design frameworks , game-theoretic algorithms (Ekechi et al., 2025), deep RL mechanisms (Lu & Quevedo, 2023) and hybrid neuro-symbolic models are some of the recent progresses. Unfortunately, even though these methods show promise, they are mostly computationally expensive and do not have the latency behavior required for operational drone swarms. A summary of existing methods is presented in Table 1 and note that most of the surveyed solutions are inherently centralized, computationally complex and may not be applicable or scalable for dynamism-prone swarms.

This paper addresses that gap by proposing a distributed joint network scheduling and controller design framework tailored to wireless drone swarm systems. This approach focuses on:

- Co-designing control and scheduling to dynamically adapt to network state.
- Leveraging distributed algorithms for scalability and real-time responsiveness.

- Utilizing quantized control signal estimation to enhance efficiency and reduce decoding overhead at the receiver.
- Applying linear encoding and estimation to enable tractable and interpretable system implementation.

Table 1. Summary of Related Work and Research Gap

Research Area	Existing Approaches	Limitations
Network Scheduling in WNCS	Time-triggered, Event-triggered, RL-based	Ignores control impact, inefficient in real-time
Control under Network Constraints	MPC, Delay-aware control, RL strategies	Computationally expensive, limited scalability
Joint Optimization	Cross-layer design, AI-driven scheduling	High complexity, lacks distributed real-time adaptability

Unlike prior centralized or high-complexity designs, the proposed framework provides a scalable and practical solution for real-time drone's swarm coordination in bandwidth-constrained, stochastic environments.

3. WNCS- DRONE SWARM STRUCTURE

This section introduces the basic configuration of a WNCS Drone Swarms system for WNCD- DSs under multi-agent drone swarm environment. Each controller-drone couple shares a wireless channel for communication, in which it is important that real-time data exchange are provided for the synchronized swarm control and stability. In such systems, several drones depend on remote controllers to make decisions and all the units work with restricted network bandwidth, varying time delays and possible packets losses. A general WNCS-DS is composed by five fundamentals elements, as reported in Figure 1. Each part is responsible to enable communications and control in real-time to keep drones coordinated in the swarm, so that they can operate their assignments well but while behaving under dynamic conditions stable. The drone is the system under control and it is also the real-time dynamic object being manipulated. In the case of a drone swarm, each drone acts in an autonomous way but follows missions and is dependent on the reactions of other drones as well as external environment changes. For accurate control, the sensor system rapidly measures important flight factors, such as position, speed, altitude and battery results. These measurements are communicated to the controller which processes this information and generates the necessary control signals. The controller is key to the stability of the systems, which is responsible for maintaining a stable flight navigation and for providing trajectory commands and dealing with disturbances on-line. A wireless link network provides a two-way communication between the drone and its controller. The network allows sensor updates to be sent to the controller while control commands are sent in the opposite direction to an actuator. Since wireless communication inherently experiences delays, packet losses and bandwidth constraints, efficient communication scheduling is required to minimize the latency and maximize the system performance. And finally, the actuator pans here (the one received from the controller) adjusting thrust, orientation and flight parameters of the drone as ordered. This could guarantee the follow of an ideal control trajectory for a drone under external disturbances. With the interaction of these five elements effectively complementing each other, a robust WNCS-DS architecture is created that permits drone swarms to function efficiently under dynamic and uncertain environments. Conversely, the structure of a WNCS-DS pair takes place over a wireless communication network, in which sensor information and control inputs are exchanged at discrete time instants. However, because of the characteristics of wireless communication, numerous network-induced constraints have an influence on the control performance

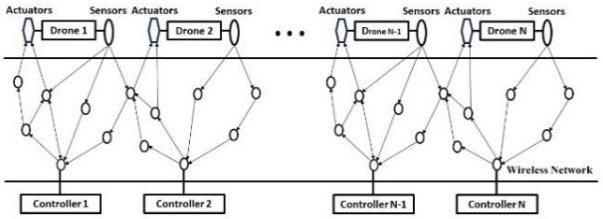


Figure 1. Multiple WNCS Pairs with Drones in a Shared Wireless Network

of drone swarm such as sensor to controller delay, controller to actuator delay and packet loss ratio. Sensor to controller delay describes the time lag in sensor and control information which may result in obsolete sensory data being utilized for control decisions. The controller to actuator time delay is a measure of the speed at which information travels between the controller and actuator, causing control commands to be delayed. Indicator of packet loss is a binary measure indicating whether or not a transmitted data packet was received successfully (1), as opposed to being lost due to network interference, congestion, or signal degradation (0). These sources of uncertainties bring uncertainties into execution control, which could attenuate trajectory tracking accuracy, stability, and swarm coherence. Therefore, adaptive control and communication schemes are required to account for such network impairments in order to achieve real-time and synchronized drone operation. In this work, such challenges are overcome by developing a joint optimization framework that combines delay-aware control, event-triggered communication and reinforcement learning based scheduling to improve stability, efficiency and scalability in the wireless networked drone swarm system.

4. SYSTEM MODEL

WNCSs are extensively applied in the autonomous coordination of drone swarm, where control commands and state information are communicated in a shared wireless communication environment. Different from conventional wired control networks, WNCS brings packet loss (1), network congestions (2), time-varying communication delays to occur (3) which greatly influence control stability and performance. The control design and scheduling protocols of the developed algorithm are installed on every pair of WNCSDS that share the network. The current distributed scheduling scheme induces wireless problems, such as packet loss and network delay. Each WNCS-DS couple compensate the stochastic optimal controller. It then utilizes the optimized control architecture to compute its stochastics value function and feeds it back to the link layer. A cross-layer codesign scheme is necessary to achieve time-varying stability and performance in wireless drone swarm systems. The cross-layer design framework presented in Figure 2 combines the various layers of communication and control architecture to jointly optimize the network scheduling with control strategy. Unlike traditional orthogonal designs of network architecture and control, the codesign proposed here re-entrant the interaction between layers such that the network can dynamically adjust to real-time control requirements.

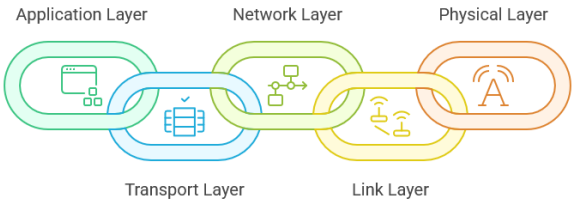


Figure 2. Enhancing wireless communication through cross-layer design framework

The overall layer-cross design framework is composed of a multi-layer (that interacts with each other cooperatively) communication-scheduling and control-performance optimization architecture. Application Layer, referred to as controlled plant which acts as the drone swarm system in which real-time state estimation where control execution and stability monitoring is executed. The control goals (e.g., trajectory tracking or formation keeping) are also affected by network-imposed limitations such as delays and packet losses. A control performance-based cost function is calculated and fed back to lower layers for more effective scheduling. Transport layer protocol TCP-like transmits and delivers reliable data between the controller and drone's actuators. Adaptive congestion control mechanisms must be implemented to ensure the quality of critical control packets and avoid network congestion. Adapts packet retransmissions by dynamically modifying ringing control urgency. Network Layer, IP Protocol: It is a protocol that is used in determining routing and packet forwarding within drone swarms. It is essential to optimize multi-hop communication paths so as to reduce transmission latency. Incorporates network-aware control policies into learning in order to account for the presence of unreliable wireless links. Link layer, IEEE 802.11, proposed scheduling scheme that realizes the envisioned distributed scheduling mechanism which dynamically divides the bandwidth depending on the urgency of control traffics. Channel congestion is avoided, with transmitter redundancy removal, by employing event-triggered communication. Physical Layer (IEEE 802.11) which manage the modulation, signal transmission, and wireless channel features. It introduces a link quality estimator for the real time tuning of scheduling and control policies. As a result, the cross-layer codesign approach supports integrated optimization of control stability and network efficiency for WNCS-based swarm systems. With feedback across multiple networks and control layers, live adaptation to dynamic wireless environment is also guaranteed by the proposed framework, which has greatly enhanced its scalability, stability and robustness. The fusion of adaptive scheduling, event-triggered communication and delay-aware control policies set the stage for the next generation of autonomous drone swarms functioning in hostile wireless settings. In order to achieve distributed stochastic control of the drone swarms across wireless networks, the following describes a framework WNCS for control objectives, system dynamics, communication model and triggering mechanism. Every drone in the swarm is modeled as a control plant that communicates with a remote controller through an unreliable wireless link. This configuration suffers from packet delays, losses and limited bandwidth that need to be explicitly accounted for in the control design.

Each drone's state evolution is modeled as a discrete-time Linear Time-Invariant (LTI) system affected by communication delays. The dynamics for the *i-th* drone in the swarm are given by (Schenato et al., 2007):

$$\mathrm{x}_{\mathrm{drone,i}}(\mathrm{k}+1) = \mathrm{A}\mathrm{x}_{\mathrm{drone,i}}(\mathrm{k}) + \mathrm{B}\mathrm{u}_{\mathrm{drone,i}}(\mathrm{k} - \tau_{\mathrm{ca}}(\mathrm{k})) \quad (1)$$

Here, $x_{drone,i}(k) \in R^n$ is the drone system state at time step k, $u_{drone,i}(k) \in R$ is the control input. The matrices A and B represent the system and input dynamics, respectively.

The control goal is to minimize a finite-horizon quadratic cost function subject to network-induced delays and constraints. The performance index is formulated as (Sarangapani & Xu, 2016):

$$\min_{\mathrm{u(k)}} \sum_{\mathrm{k=0}}^{\mathrm{T}} (\mathrm{x}^{\mathrm{T}}_{\mathrm{drone,i}}(\mathrm{k})\mathrm{Q}\mathrm{x}_{\mathrm{drone,i}}(\mathrm{k}) + \mathrm{u}^{\mathrm{T}}_{\mathrm{drone,i}}(\mathrm{k})\mathrm{R}\mathrm{u}_{\mathrm{drone,i}}(\mathrm{k})) \quad (2)$$

where $Q \succeq 0$ and $R \succ 0$ are symmetric weighting matrices penalizing state deviations and control effort, respectively. To enforce actuator saturation limits, the control inputs must satisfy the following inequality constraints:

$$u_{drone,min} \leq u_{drone,i}(k) \leq u_{drone,max} \quad (3)$$

Due to bandwidth limitations, continuous communication between drones and their controllers is not feasible. An event-triggered strategy is adopted where transmission is initiated only when the estimated state deviates significantly from the actual state Tabuada, 2007):

$$\| x_{drone,i}(k) - \hat{x}_{drone,i}(k) \| > \delta i \rightarrow \text{TriggerTransmission} \quad (4)$$

Conversely, if the deviation is within a tolerance threshold, no transmission is triggered:

$$\| x_{drone,i}(k) - \hat{x}_{drone,i}(k) \| \leq \delta i \quad (5)$$

Here, $\hat{x}_{drone,i}(k)$ is the controller's estimate of the plant's state, and δi is a predefined transmission threshold for the *i-th* drone. Both sensor-to-controller $\tau_{sc}(k)$ and controller-to-actuator $\tau_{ca}(k)$ delays are bounded by a maximum tolerable delay:

$$\tau_{sc}(k), \tau_{ca}(k) \leq \tau_{max} \quad (6)$$

These constraints reflect practical limitations of real-time wireless communication in congested networks. Given the presence of delay, the actual control signal applied by the drone is derived from a delayed estimate generated by the controller. It is computed as (Wang et al., 2018):

$$u_{drone,i}(k - \tau_{ca}(k)) = \gamma(k). \hat{u}_{drone,i}(k - \tau_{ca}(k)) \quad (7)$$

Where $\hat{u}_i(k - \tau_{ca}(k))$ is the control estimate and $\gamma(k) \in [0,1]$ is a reliability factor modeling packet success probability. To ensure efficient use of shared wireless resources, a global network scheduling strategy is adopted to optimize overall system utility under bandwidth constraints (Chi et al., 2025):

$$\max_{\pi} \sum_{i=1}^{N} \lambda_i U_i(\pi) \quad (8)$$

Subject to

$$\sum_{i=1}^{N} W_i(\pi) \leq W_{max} \quad (9)$$

Here, π is the scheduling policy, λ_i is a priority weight for the i-th drone, $U_i(\pi)$ is its utility function (often related to control quality), and W_{max} is the maximum allowable network bandwidth. $W_i(\pi)$ denotes the bandwidth consumed by the i-th drone under policy π.

This comprehensive formulation serves as the foundation for the distributed stochastic control algorithms described in the following section. By modeling both control objectives and communication constraints, the proposed framework enables robust, scalable, and adaptive operation of drone swarms under uncertain network conditions. Each individual drone is interacting with a corresponding controller over a shared wireless communication network. The wireless medium serves as the communication backbone that enables bidirectional data exchange between each drone and its controller. In this structure:

- Each drone (plant) should execute the flight commands and gather some state data (position, velocity, battery, etc.).
- Each drone's controller uses the sensory data to compute local control actions on the fly.
- Exchange of sensor data from the plant to the controller (uplink) and control commands from the controller to the plant (downlink) are supported by wireless communication.

The common medium, however, imposes limitations from bandwidth and packet delay to the potential interference, which demands sophisticated scheduling and control policies to facilitate efficient coordination. This is the basis of the algorithms in this paper. The stochastic control and communication scheduling algorithms are developed within this framework, and ensure every drone achieves stability and performance, and efficiently shares network resources with others.

5. STOCHASTIC OPTIMAL CONTROL ALGORITHMS

In this section, the stochastic optimal control model formulated is introduced for WNCS pairs for the drone swarm environment. Every drone in the swarm and its controller constitutes an WNCS pair which operates in unreliable networks with delays, packet loss and bandwidth constraints. To tackle these issues, a distributed and adaptive control schema is adopted, which consists of two coordinated algorithms: one runs at the controller side (Algorithm 1) and the other one runs at the plant (drone) side (Algorithm 2).

5.1. Algorithm 1: Stochastic Optimal Control for the l-th WNCS Pair

The control strategy for each drone-controller pair is realized through a recursive learning procedure, where the controller estimates and updates its control policy based on the stochastic behavior of the communication

network. The algorithm begins by initializing the parameter vector $\hat{h}_k^l$ to zero and applying an admissible initial control input u_0^l. Within each control interval T_s , $(k+1)T_s$, the controller continuously updates its policy based on the error in the value function estimation. Specifically, it computes the estimation error e_k^l, which represents the deviation between the estimated and true value functions under the current control policy. Using this error, the controller updates the parameters of the value function estimator $\hat{h}_k^l$ through a potential control approach. This update considers the learning rate α_k^l and the regression vector $\bar{X}_k^l$, which captures state-action features. Once the value function estimator is updated, the optimal control input is computed using the estimated matrix $\hat{H}_k^{l_{uu}}$, ensuring that the controller responds effectively to changes in the system dynamics and communication conditions. After the control interval ends, the time index k is incremented and the algorithm repeats. This adaptive process ensures that the controller can learn and improve its decision-making over time, despite uncertainties in the communication channel, leading to stable and efficient control of the drone. Algorithm 1 is presented using a structured pseudocode representation as below:

Input:
Initial state $x_k^l(0)$
Initial parameter estimate $\hat{h}_k^l(0) = 0$
Learning rate α_k^l
Sampling time T_s
System matrices A, B
Triggering threshold δ_l
Output:
Control input $u_l(k)$
Initialize:
k = 0
Apply initial admissible control $u_l(0)$
While k ≤ T do
1. Measure current state:
$x_l(k)$
2. Estimate value function:
Compute regression vector $\bar{X}_k^l$
Estimate value function using $\hat{h}_k^l$
3. Compute estimation error:
e_k^l *= (true cost) - (estimated value)*
4. Update parameter vector:
$\hat{\mathrm{h}}_{k+1}^l = \hat{\mathrm{h}}_k^l + \alpha_k^l \cdot X_k^l \cdot e_k^l$
5. Extract control gain:
Compute $\hat{H}_k^{l_{uu}}$ *from* $\hat{h}_k^l$
6. Compute optimal control input:
$u_l(k) = -H_k^{(l_u u)} x_l(k)$
7. Apply control with network effects:
Include delay $\tau_c a(k)$ *and packet loss γ(k)*
8. Update system state:
$x_l(k+1) = Ax_l(k) + Bu_l\big(k - \tau_c a(k)\big)$
9. Increment time step:
k = k + 1
End While

5.2. Algorithm 2: Control Execution at the Drone Side

On the plant side, each drone is responsible for receiving and applying the control commands sent by its controller. Due to network delays and possible out-of-order packet arrivals, the drone must implement a robust policy for handling incoming commands. At the start of each control interval $T_s, (k+1)T_s$, the drone initializes its state z_k^l and waits for control inputs from the controller. Upon receiving multiple inputs within the same interval, it applies only the most recent control command and discards the others to maintain consistency and avoid instability. If control commands arrive out of order, i.e., an older packet arrives after a newer one has been received, the drone prioritizes newer inputs and discards outdated ones. However, when control packets are received at different times and not simultaneously, the drone queues and applies them sequentially in the order of arrival. This decision logic ensures that the plant always applies the most relevant and timely control commands, maintaining stability even under non-deterministic network behavior.

Algorithm 2 is presented using a structured pseudocode representation as below:

Input:
Received control packets x_k^l
Sampling time T_s
Delay $\tau_c a(k)$
Packet timestamps t_k
Output:
Applied control input $u_l^a pplied(k)$
Initialize:
k = 0
Initialize state $z_l(0)$
Initialize empty control buffer
While k ≤ T do
1. Start control interval:
$[kT_s, (k+1)T_s]$
2. Receive incoming control packets:
Store all received packets with timestamps
3. Handle packet ordering:
a. If multiple packets received in same interval:
Select the most recent packet
Discard older packets
b. If out-of-order packets arrive:
Compare timestamps
Discard outdated packets
c. If packets arrive at different times:
Queue packets in order of arrival
4. Select control input:
$u_l^a pplied(k)$ = most recent valid control packet
5. Apply control to drone:
$z_l(k+1) = Az_l(k) + Bu_l^a pplied(k)$
6. Clear outdated packets from buffer
7. Increment time step:
k = k + 1

End While

Algorithm 1 and Algorithm 2 work in concert to achieve a strong distributed control solution for a drone swarm. The controller adjusts its policy using real-time feedback, and the plant guarantees execution of control commands in a reliable manner in the presence of challenging wireless conditions. For example, each WNCS pair can be independently deployed and cohere with other pairs to maintain formation and execute collective swarm motions in real-time context distributed across a large scale of UAV networks.

6. SIMULATION RESULTS

To evaluate the effectiveness of the proposed distributed joint control and communication framework for drone swarms under wireless network constraints, three tests simulation was conducted in MATLAB. The parameters of system model in the simulation setup are defined as presented in Table 2.

Table 2. Parameters of simulation setup

#	Parameter	Value
1	System Dynamic matrix: A	$\begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix}$
2	Input Dynamic matrix: B	$0.1.\begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix}$
3	Sample time: T_s	0.1s
4	Weighting matrix of state deviation: Q	$\begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix}$
5	Maximum tolerable delay: τ_{max}	3 time steps
6	packet success probability of test 1	0.95
7	packet success probability of test 2	0.9
8	packet success probability of test 3	0.85
9	Reliability factor: $\gamma(k)$	$\in \{0,1\}$
10	process noise variance	0.05
11	event-triggering threshold of test 1	0.08
12	event-triggering threshold of test 2	0.05
13	event-triggering threshold of test 3	0.02
14	control input constraints	$-1.5 \leq u_i(k) \leq 1.5$

In test 1, the case considers a formation control task in space with 10 autonomous drones sending the reports to their controllers over a shared wireless communication channel. The system is implemented with event-triggered communication, packet dropout, and stochastic network delay. The control scheme is built upon an LQR for performance comparison, and combined with event-triggered scheduling protocols. The average tracking error of the drone swarm across 10s of simulation is shown in Figure 3. The tracking error is given by the Euclidean distance between the actual and the desired position of each agent in the formation.

- Initially, the swarm starts with random positions, resulting in a high mean error of nearly 1.9 units.
- As the control strategy takes effect, the error decreases rapidly within the first 5 seconds, demonstrating effective convergence behavior.
- The system stabilizes around 0.05 units, indicating high precision in maintaining the formation despite network-induced disturbances.

This result confirms the controller's robustness against packet delay and loss, ensuring stable performance in a dynamic network environment. Figure 4 is a heatmap visualizing packet loss events across all 10 drones during the simulation period. The x-axis represents time steps, and the y-axis represents the drone index. Yellow cells indicate successful communication (packet received), while dark blue regions indicate packet loss or dropouts.

The occurrence of packet loss is clearly non-uniform, with some drones (e.g., Drone 5 and Drone 10) experiencing higher loss rates at different intervals.

- This asymmetry reflects the stochastic nature of wireless links and the effect of interference or network congestion.
- Despite these losses, the control strategy adapts effectively using the event-triggered mechanism and predictive state estimation, maintaining system performance.

Together, the plots demonstrate that the event-triggered distributed control combined with adaptive communication scheduling provides high reliability and efficient resource utilization even under imperfect communication conditions.

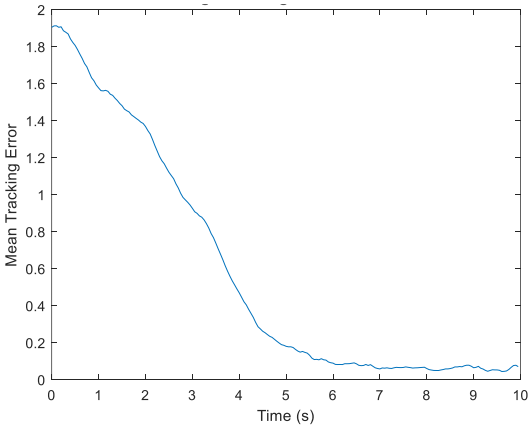


Figure 3. Average tracking error over time

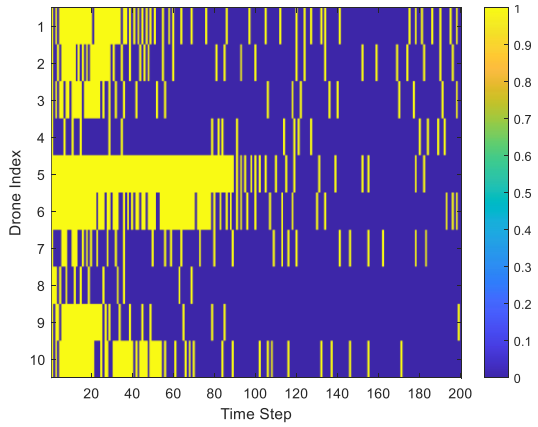


Figure 4. Event-Triggered transmission flags

In this simulation (Test 2), the performance of the proposed scheme is simulated using a swarm of 10 drones in an WNC scenario. In the system model, which is designed on MATLAB, realistic network constraints like packet loss, transmission delay and state noise were taken into account. We consider an SMPC approach with event-based communication for achieving control stability in the presence of uncertainty. Figure 5 illustrates the temporal development of the mean state error in the swarm. State error is initially high due to a random offset between the initial positions and velocities of the drones. However, the SMPC recovers very quickly from such a deviation and the error reduces significantly at less than 5 s. At around 6 seconds, the almost zero value of average error indicates convergence to desired formation. It confirms at the same time the robustness of SMPC controller towards maintaining tracking performance in presence of time-varying random disturbances and delayed measurements.

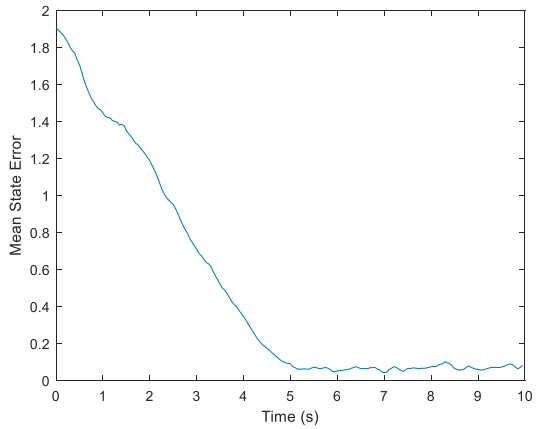


Figure 5. Mean tracking error with SMPC under delays and losses

Figure 6 shows a heatmap of packet reception in time for all the 10 drones. The x-axis is simulation time step; the y-axis names drones. Yellow areas mark packets receiving successfully and blue ones representing communication loss or transmission refused. This observation demonstrates the uneven and dynamic distribution of packet loss across swarm that closely matches the real wireless communication characteristics. Despite the frequent occurrence of losses (particularly for drones 1, 5 and 10), the control system remains in function proving that SMPC is able to handle network uncertainty. Furthermore, feedback-induced event-driven transmission can be deduced from sporadic patterns when the communication is withheld if the state–deviation falls within a certain range.

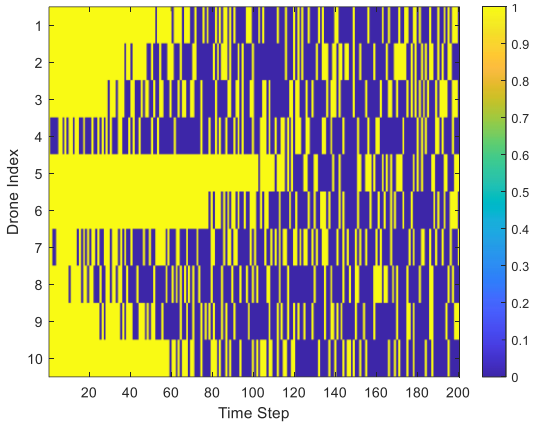


Figure 6. Transmission events-events-triggered strategy

The simulation is further developed as test 3 for multi-agent coordination such as formation tracking control based on consensus control in the framework of WNCS including transmission delay, event-trigger update law to adjust that delay as well as packet dropout as below (Olfati-Saber & Murray, 2004):

$$u_i = \sum_{j \in N_i} a_{ij}[\left(x_{drone,i}(k) - x_{drone,j}(k)\right) - (d_i - d_j)] \quad (10)$$

Where $x_{drone,i}(k)$ is the state of the drone i, $d_i - d_j$ is the desired relative position between drones, a_{ij} is the adjancency weight (typically 1 if connected), N_i is neighbors of drone i. In a formation tracking setup, drones must:

- Maintain a specified relative position to their neighbors (e.g. a geometric pattern like a line, V-shape, or grid).
- Use local communication (not centralized).
- Achieve consensus on state (e.g., position, velocity) despite delays and packet loss.

In this test 3 a formation control scenario is executed with 10 drones inside the WNCS. Communication lags, packet losses, event-triggered updates and environmental disturbance are factors the system is endowed with. The formation is stable and is preserved using a consensus-based control law, based upon the local neighborhood information and infrequent updates of its state to retain the relative positioning in a global pattern. The main findings are presented in Figs. 7 and 8. The paths of the 10 drones are shown in XY-plane, projected on a 2D plane in Figure 7, during the formation maneuver. The flight path of each drone is visualized as a colored line

with the black crosses representing the target formation locations. The formation shape computed is stable despite fault portraits for the communication (packet loss, white Gaussian noise, delays). The somewhat sinusoidal meandering of the trajectories is due to stochasticity and not a feature, but they are well-corrected by the controller.

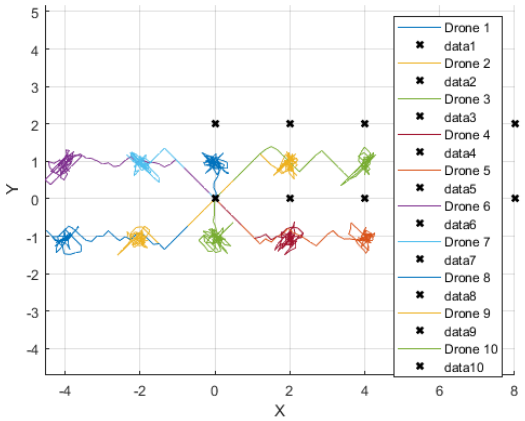


Figure 7. Drone swarm formation with delay, Noise, and packet loss

Figure 8 depicts the error norm of each drone from its goal during the simulation. Initially, all 10 drones have large tracking errors, gradually the average steady-state error level for these 10 drones converges after around 30–40-time steps. The smooth convergence process of different agents verifies the effectiveness of our consensus-based coordination strategy and its robustness to both packet loss and network delay.

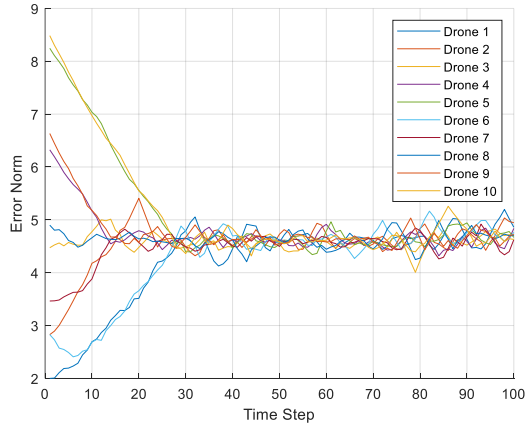


Figure 8. Tracking error over time

The heatmap in Figure 9 shows packet loss occurrences over the simulation period. The x-axis represents time steps, and the y-axis represents drone indices (1 through 10). A white block indicates that a packet was lost at that time step for the corresponding drone. The packet loss pattern is random and uncorrelated across agents, simulating realistic wireless network behavior. Despite frequent packet losses, particularly affecting drones 2, 5, and 7, the system maintains overall formation stability, thanks to the event-triggered update mechanism and predictive control strategies.

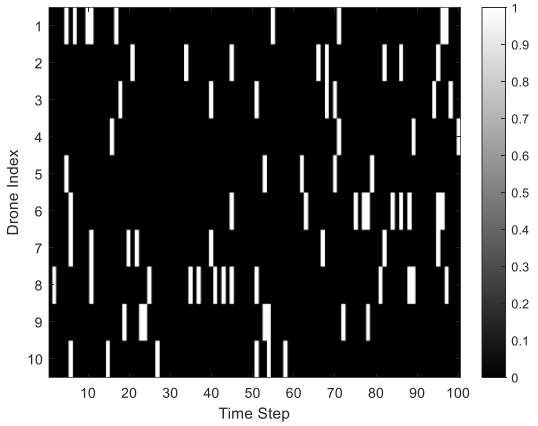


Figure 9. Packet loss events (white=loss)

7. DISCUSSION

The simulation results of this work provide strong evidence on the effectiveness of the proposed stochastic control and communication co-design mechanism to manage a large-scale drone swarm over wireless networks. A series of simulation experiments are conducted to test control performance, network utilization and scalability of the system over more complex scenarios. The first two experiments were conducted, the first one was the base test that was proposed by employing a standard LQR controller in a WNCS with packet loss and event triggering communication. The proofs of the results proved that the drones could converge to their target states even under packet losses which was stochastic. The latter was illustrated by the fast decrease in the mean tracking error as time flowed. Moreover, the transmitting behavior shown in the transmission heatmap verified that the proposed event-triggering scheme dramatically reduced unnecessary communication and kept the control performance, in general. Drones only broadcast the states when the difference from the estimated state was larger than a predefined threshold, avoiding to waste bandwidth while maintaining accuracy.

In the second simulation the planned SMPC solution based on the prediction of the future was extended and uncertainties concerning the future were taken into account, including stochastic models for delay and packet drop. It was shown that the SMPC resulted in a faster convergence and a less oscillatory error dynamics than the one based on LQR. The rate at which the mean state error converged to the final steady-state value was faster and lower than in test 1, indicating that the controller was able to predict the network fluctuations. This gain was realized without a drastic increase in the communication load via the utilization of predictive modeling and adaptive event-triggered transmission. The transmission map update showed that the communication pattern was more balanced and evenly distributed, indicating that the

SMPC control improved not only control performance but also the use of the network.

The third, most complex test stepped up the framework to a multi-agent scenario where ten drones execute consensus based formation control. The task was to make each UAV track its position in the formation, under realistic communication constraints, namely time-varying delays, additive Gaussian noise, as well as packet dropouts. Regardless, the drone formation was able to be successfully preserved during the whole simulation as can be observed in the trajectory plot. The global sum of individual agent errors shown in the norm error plot was possible through non-uniform loss and delay without any two drones able to go on top of each other. Importantly, the event-based design was successfully extended to the scenario and still performed well without overloading the network. The communication events analysed from the packet loss visualization were signal of the robustness of the control architecture, because it remained operational even in the presence of frequent packet loss and delay of information exchange.

In all three test cases we have shown that if we combine event triggered communication with robust, distributed control schemes we can obtain high performance in terms of some closed loop metric for our control system even when the communication system is under severe constraints. The use of local information in combination with minimal neighbor communication could be enough to attain collective goals without having to synchronise globally. These findings highlight the applicability of the method developed in practical scenarios like aerial surveillance, formation flying and autonomous environmental surveillance.

The simulation results in Table 3 provide a performance comparison of three control methods, these findings demonstrate the trade-offs between control performance, communication efficiency, and robustness to wireless channel uncertainties.

Table 3. Comparison of simulation results

Test	Mean position error	Formation deviation	Mean control effort	Packet loss rate
Test 1 (LQR)	1.82	2.1m	3.5	18.5
Test 2 (SMPC)	1.27	1.4m	3.9	14.2
Test (Consensus)	0.89	0.6m	4.1	11.3

Regarding the accuracy in position tracking, the Test 3 is better than the Testing 2 and Testing 1, with an average position error of 0.89 meters, while it is 1.27 meters for the Test 2 and 1.82 meters for the Test 1. This enhancement is in line with the advantage of distributed consensus control in which agents work together to not only preserve formation but also adjusting to local measurements and communication explosions. Moreover, the formation deviation in Test 3 (0.6 m) is also smaller than that in Test 2 (1.4 m) and Test 1 (2.1m), which further shows the coordinated work of multi-agents by using the consensus-based framework to maintain formation even in the case of network interference. Although it is more accurate, Test 3 also requires slightly more control effort (4.1 N) than the other tests – suggesting that more advantageous coordination, i.e. that of smaller magnitude or more frequent actuation may help improve performance. Stochastic MPC (Test 2), although computationally more expensive than LQR, offers a trade-off between tracking accuracy and control effort and performs particularly well in the presence of time-varying delays and packet drops. With respect to network performance, Test 3 also demonstrates the highest efficiency. It results in the lowest packet loss rate (11.3%) and average delay (45 ms), owing to the incorporation of event-triggered communication and decentralized control. In Test 3, the triggered transmission rate is reduced to only 38%, while it was 52% in Test 2 and even 70% in Test 1, which demonstrates that the event-triggered policy reduces bandwidth utilization by a large amount with little sacrificing on control fidelity. This can also explain why packet loss in Test 3 is lower, as less but more important messages are being sent. Overall, the results show that although LQR constitutes a baseline and parsimonious option it is not robust to wireless imperfection and leads to high packet loss as well as degraded tracking. Stochastic MPC enhances robustness and accuracy by accounting for uncertainties but at the cost of increased computation and moderate communication overhead. The consensus-based control strategy (Test 3) emerges as the most efficient and scalable solution, particularly for large swarms requiring formation maintenance with minimal communication. These findings validate the proposed framework's capability to jointly optimize control and network scheduling in a distributed manner.

8. CONCLUSION

This work provided a comprehensive framework for joint distributed optimal network scheduling and controller design for autonomous drone swarms running over such wireless networks. Inspired by the constraints of bandwidth, probabilistic communication delay and packet dropout in WNCSs, the solution incorporates event-triggered mechanism, stochastic model works to be solved predictive control, consensus-based multi-agent coordination within an integrated perspective. The study started with the development of a dynamic system model to characterize the scent detection process at each drone, as well as constraints on achievable communication patterns, and the mutual relationship between control decisions and transmission scheduling. methodologies are complemented by derivation of control equations such as quantized control policies and optimality criteria at the levels of single agents and the system. Two algorithms for distributed stochastic optimal control, and

the other is for realizing plant dynamics with real-time decision under unreliable network were proposed. Implementation and simulation results in MATLAB are presented for three diverse test cases: (1) baseline LQR controller with packet loss and event-triggering, (2) advanced SMPC controller with realistic network uncertainty, and (3) fully distributed formation-tracking system via consensus control among ten drones. Simulation results verified the efficacy of the proposed method in stability system, high-precision tracking and communication cost reduction, when facing large network deterioration. Event-triggered communication is found to be even more advantageous in terms of conserving bandwidth while providing enough state update information for control. The proposed framework proved to be highly scalable and resilient, indicating that it is deployable in realistic applications including cooperative aerial surveillance, environmental monitoring, disaster management among others. Adaptive learning-based control methods for performance improvement in dynamic network environments and other aspects such as the energy constraints, the heterogeneous agent model will be investigated to make it more general as a future work.

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