Layered Resilience for Perimeter Surveillance: PT/DT Architecture with Circulating Drones

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***Abstract*—Perimeter surveillance of critical infrastructure [1] demands autonomous drone architectures that maintain coverage under adversarial asset loss while preserving operational security. We present a hybrid Physical Twin / Digital Twin (PT/DT) coordination framework for circulating drone networks operating under strict furtivity constraints. PT drones execute identical distributed density-balancing algorithms using only local neighbor perception—with no inter-drone messaging—to achieve emergent coverage through adaptive spacing and velocity modulation. The DT maintains suppletive fleet state estimation via dead-reckoning and exception-only telemetry (loss events, intrusion detections), runs event-driven predictive simulations using the same PT control law, and conditionally stages spares at gap midpoints when forecasted density variance or coverage violate mission thresholds.**

Critically, DT interventions remain silent: spare drones self-insert into the patrol circuit as physical actions rather than explicit commands; PT drones perceive newcomers as neighbors and absorb them through local balancing, unaware of centralized coordination. This architectural decomposition delivers layered resilience—rapid distributed self-adaptation for minor disruptions, threshold-based spare staging for severe losses—while satisfying autonomy-first principles (no teleoperation, local decision-making authority), furtivity (exception-only RF signatures), and communication efficiency (sparse telemetry, no continuous supervisory messaging) [2].

I. Introduction: An MBSE Approach to Resilient Surveillance

Modern security operations for critical infrastructure require persistent **surveillance**, robust **resilience** against hostile environments (e.g., wildfires, intelligent adversaries), and high **credibility** in autonomous decision-making. Resilience is a fundamental requirement for ensuring the operational continuity of collaborative systems, particularly drone fleets. Resilience is defined as a system's ability to withstand disruption, adapt and recover from it [3]. Traditional approaches to risk management rely primarily on the design phase, which limits their effectiveness in dynamic and evolving environments [4], [5].

Digital twin (DT) emerged to meet the need to control, predict behaviours, improve maintenance, ensure the continued operation of an actual system. A DT is defined as a virtual representation of an actual twin that can be a physical object, a process, or a system, enabling real-time performance monitoring, behaviour simulation, and usage optimization through real-time data [6]. A DT, in addition to being a representation of its AT, can have the ability to send data and act directly on the AT. This ability allows it to improve the efficiency of the decision-making process, optimization and problem-solving. By leveraging DTs, organizations can improve their performance through predictive maintenance or system optimization and enhanced decision-making capabilities.

By leveraging DTs, organizations can improve their performance through predictive maintenance or system optimization and enhanced decision-making capabilities. These virtual replicas enable testing and validation, allowing organizations to simulate scenarios, anticipate challenges, and implement solutions proactively. A significant advantage of incorporating DTs lies in their ability to facilitate continuous improvement. Through iterative testing and automation, companies can refine processes and products, achieving higher levels of efficiency and quality. The capacity for real-time monitoring ensures that organizations can respond to changing operational conditions swiftly, minimizing downtime and operational risks. The use of digital twin allows for on-the-fly prototyping of scenario exploration, remediation strategies and assessing their effectiveness, using simulation and modelling of system behaviour under normal and disrupted conditions, taking into account different sources of disruption. The digital twin can thus be used to test different system configurations and anticipate potential failures.

The development of DT has been widely explored in industry and in various fields [7]. An ISO standard [8] describes the fundamental principles of a framework for industrial DT. Models [9] and architectures, such as DT RAMI 4.0 [10], exist as well as software development platforms offered by major software publishers. The number of publications is increasing on this subject, mainly in the industrial field. The issues related to the

use of a DT mainly focus on how to use this technology to model the system, detect potential disturbances and predict their undesirable effects, deploy resilience policies, while integrating it into the daily management of the RS (maintenance, etc.).

A. Application Domain: Drone-Based Perimeter Surveillance

This work focuses on **perimeter surveillance** as its primary application domain, where critical infrastructure (power plants, military installations, sensitive facilities) requires continuous monitoring against intrusions and threats. Drone fleets are particularly well-suited to this mission: they provide mobile, reconfigurable surveillance capabilities that can adapt to failures, scale to large perimeters, and maintain persistent coverage without fixed infrastructure. Unlike stationary sensor networks, circulating drones offer inherent resilience through motion and redundancy, while their communication-minimized operation supports both operational efficiency and tactical discretion. The integration of DT technology with such autonomous drone fleets raises fundamental questions about architecture, control distribution, and the balance between local autonomy and global coordination—questions this paper addresses systematically.

B. Contributions

This work makes two complementary contributions, detailed in Section III:

1) **Loosely-coupled PT/DT architecture**: An architectural paradigm enabling furtive autonomous operations through asymmetric coupling—*Physical Twin* (PT) executes fully autonomous distributed control while *Digital Twin* (DT) provides event-driven predictive oversight and conditional spare staging, without continuous communication or explicit commands.
2) **Empirical scalability validation**: Quantified evidence that the PT/DT architecture scales from research prototype ($n = 20$ drones) to country-scale deployments ($n = 10{,}000$ drones), with findings on sensing economics, failure resilience, computational feasibility, and deployment viability.

The evaluation methodology underpinning these contributions—Design-Space Exploration (DSE) for systematic comparison of architectural and algorithmic alternatives—is presented in Section II. The PT/DT architectural decomposition and coupling mechanisms are formally introduced in Section IV.

C. Requirements and Constraints

A comprehensive list of requirements for the system (i.e., conditions or capabilities that the system must fulfill to achieve its objectives) is itemized below, organized by lifecycle stage:

a) Design Time:

- $R^{\circ}_{DT}1$: **Domain Space Exploration (DSE)** shall support prescriptive design by expressing architectural alternatives and exposing measurable trade-offs (e.g., performance vs. cost) of the whole system.
- **Non-Functional Requirements (NFRs):**
  - $R^{\circ}1$: **Scalability** — System capability must grow no more than linearly with asset size.
  - $R^{\circ}2$: **Reliability** — High confidence in detection with low false positives.
  - $R^{\circ}3$: **Resilience / Survivability** — The system shall maintain service availability despite failures.

b) Operation Time:

- $R^{\circ}_{OT}1$: **Continuous Coverage** — Critical assets must be protected by ensuring 24/7 surveillance.
- $R^{\circ}_{OT}2$: **Trusted Detection** — Undesired events are reported based on reliable detection.
- $R^{\circ}_{OT}3$: **Appropriate Response** — The system must enable timely and effective countermeasures.
- **Operational Constraints:**
  - $C^{\circ}_{Op}1$: **Tactical Autonomy** — Operational needs must be fulfilled automatically at the tactical level.
  - $C^{\circ}_{Op}2$: **Human-Centric Strategy** — High-level strategic decisions (e.g., resource reallocation) must remain under human control (human-in-the-loop).

c) Deployment Time:

- **Deployment-time objective:** initialize the system (fleet size, waypoint geometry, initial spacing, DT thresholds) so that the subsequent mission can run autonomously.
- $C^{\circ}1$: **Resilience / Survivability** — Maintain service availability despite partial degradation (for example the loss of a drone).
- $C^{\circ}2$: **Parsimony / Efficiency** — Cost-effective operation for indefinite mission durations (energy/asset optimization).
- $C^{\circ}3$: **Furtivity / Low Observability** — In military or adversarial contexts, this extends to avoiding detection by adversaries. It means that the communications must be limited to the necessary.

Table I maps requirements and constraints that directly drive architectural design decisions. Functional outcomes (e.g., continuous coverage $R^{\circ}_{OT}1$, trusted detection $R^{\circ}_{OT}2$, appropriate response $R^{\circ}_{OT}3$) and meta-requirements (e.g., DSE support $R^{\circ}_{DT}1$, human-centric strategy $C^{\circ}_{Op}2$) are realized as emergent properties

through the combination of these architectural choices rather than standalone design responses.

Table I
TRACEABILITY FROM REQUIREMENTS AND CONSTRAINTS TO ARCHITECTURAL RESPONSES

Stage	ID	R /C	Architectural Response
Design	$R^\circ 1$	Scalability	Distributed control; modular fleet structure; teleoperation-free operation
Design	$R^\circ 2$	Reliability	Redundant sensing; confidence scoring; event qualification
Design	$R^\circ 3$	Resilience, Survivability	Scenario-based dimensioning; circulating assets; self-organization; on-demand spare deployment
Operation	$C^\circ_{Op}1$	Tactical autonomy	Local adaptation; algorithmic control laws; implicit support request
Operation	$C^\circ 2$	Parsimony, Efficiency	Exception-only communications; energy-aware control
Deployment	$C^\circ 3$	Furtivity, Low observability	Silent by default; event-triggered RF; semantic filtering (qualified events only); optional cross-confirmation for intrusions (not for loss/destruction)

D. From Requirements to Architecture

Given the drone-based perimeter surveillance context, the core challenge is to design a system architecture that fulfills three key objectives: (1) surviving component loss, (2) identifying threats furtively, and (3) providing decision-makers with the necessary strategic awareness to act when required.

The fleet operates as a **system of systems (SoS)**: each drone has its own autonomy, decision-making system, and geographical position, yet they must coordinate collectively to accomplish the surveillance mission. The requirements enumerated above—persistent coverage ($R^\circ_{OT}1$), resilience to losses ($R^\circ 3$), scalability ($R^\circ 1$), tactical autonomy ($C^\circ_{Op}1$), and furtivity ($C^\circ 3$)—drive the following architectural choices:

a) Architectural Choices::

- **Circulating Architecture for Positional Furtivity** Mobile assets in constant motion create a dynamic, unpredictable surveillance screen, enhancing both resilience and furtivity.
- **Event-Triggered Communication:** To minimize RF signature, assets communicate only mission-critical exceptions, not nominal status updates.
- **Autonomy-First Design:** Local decision-making authority is essential for scalability; teleoperation is unscalable at large fleet sizes.
- **Hybrid Control Loop:** A distributed fleet is complemented by a global reasoning layer, providing strategic situational awareness and supporting human-in-the-loop decision-making.

b) Logical Components::

- **Field Observer:** Responsible for data acquisition, information extraction, event qualification, and exception-based reporting.
- **Global Reasoner:** Maintains global situational awareness, simulates reaction scenarios, and supports strategic decisions (e.g., asset injection, resource reallocation).

c) Physical Implementation::

- **Patrolling Drone Fleet:** At the implementation level, the system is realized as a fleet of drones following deterministic trajectories, relying on neighbor-only awareness, and self-adapting to losses.
- **Communication Policy:** ”Silence by default”—only exceptions (loss, intrusion) are reported.

II. PROPOSED APPROACH AND SYSTEM OVERVIEW

This section bridges the requirements of Section I to the detailed technical parts that follow. We first present the hybrid DT/PT architecture (Contribution 1) that is designed offline and realized at deployment/operation time. We then explain the evaluation principle (Design-Space Exploration) that motivates our empirical validation campaign (Contribution 2).

A. Evaluation Principle: Design-Space Exploration (DSE) for Architectural Validation

A dedicated evaluation environment (simulation/emulation) enables the designer to:

- **Explore architectural alternatives:** Vary the structure, size, and perception range of mobile assets or agents to study their impact on system-level properties letated to missions.
- **Experiment with control algorithms and parameters:** Test different local rules, coordination mechanisms, and behavioral parameters to assess their influence on emergent behaviors.
- **Analyze results across multiple metrics:** Quantitatively evaluate each candidate design using metrics such as coverage, resilience, scalability, efficiency, and responsiveness.

The DSE campaign systematically explores the relationships between **fleet constitution** (number of drones, initial spacing, spare availability), **hazard scenarios** (single loss, cascading failures, adversarial intrusions), and **mission outcomes** (coverage maintenance, recovery time). This parametric exploration produces dimensioning guidance: given expected hazard frequencies and

required resilience levels, what fleet size and spare inventory suffice to maintain acceptable coverage?

Full experimental protocols, scenario definitions, and simulation implementation details are presented in Section VI. This section focuses on the architectural design that emerges from DSE findings.

B. Decision Support from Evaluation Outputs

Simulation outputs are systematically analyzed to:

- **Identify trade-offs and Pareto-optimal solutions:** Balance competing objectives and constraints based on stakeholder priorities and mission context.
- **Support data-driven design decisions:** Justify architectural and algorithmic choices with explicit, reproducible evidence from simulation results.
- **Enable iterative refinement:** Use feedback from simulation analysis to iteratively improve system design before implementation.

a) Stakeholder context:: The primary stakeholders are surveillance mission personnel, ranging from strategic decision-makers (who allocate budgets, approve deployments, and authorize asset replenishment) to tactical operators (who monitor system health, interpret intrusion alerts, and manage spare deployments). DSE outputs serve both groups: decision-makers receive cost-performance trade-off analyses and fleet dimensioning recommendations, while operators gain validated thresholds for DT intervention triggers and spare staging criteria.

This evaluation-driven process ensures that the selected architecture and controller parameters are reviewer-auditable and tailored to the intended operational context, providing a rigorous foundation for subsequent implementation and deployment. The DSE outputs function as a **dimensioning manual**: given an operational environment characterized by perimeter size, expected hazard rates (loss frequency, intrusion likelihood), and mission requirements (minimum acceptable coverage, maximum tolerable gap duration, energy constraints), the analysis prescribes appropriate fleet size, spare inventory, and DT intervention thresholds.

b) Key DSE Outputs: **(a) Spare Injection Threshold Determination:** A critical result of the DSE campaign is the empirical calibration of **spare injection fire thresholds**—the conditions under which the DT must deploy spare drones to prevent coverage collapse. Through systematic exploration of failure scenarios across fleet sizes, the analysis identifies:

- **Coverage floor threshold (C_{critical}):** Minimum acceptable coverage level below which mission viability is compromised (typically $C_{\text{critical}} = 0.85$–$0.90$ depending on threat model).
- **Density variance threshold ($\sigma^2_{\max}$):** Maximum tolerable formation imbalance indicating imminent gap formation.
- **Minimum fleet size ($n_{\min}$):** Critical fleet size below which distributed self-adaptation fails and cascading losses become probable.
- **Adaptation window (T_{adapt}):** Time horizon for predictive simulation to forecast whether PT self-organization suffices or spare deployment is necessary.

These thresholds are *not architectural constants*—they emerge from scenario-specific trade-offs between reactivity (early spare deployment reduces coverage gaps but consumes inventory) and parsimony (delayed deployment conserves spares but risks coverage loss).

(b) Fleet Dimensioning Guidance: The DSE campaign quantifies the relationship between mission requirements and fleet configuration. For a given perimeter length P and required coverage level C_{target}, the analysis determines minimum viable fleet size $n_{\min}(P, C_{\text{target}})$ and recommends spare inventory levels n_{spare} as a function of expected hazard frequency. Section VII demonstrates that these dimensioning functions exhibit scale-dependent properties: larger fleets achieve better per-drone efficiency but require tighter coordination thresholds, while baseline fleets tolerate coarser control but face higher relative vulnerability to losses.

Detailed metric definitions (coverage formulation, resilience submetrics, scalability measures) and experimental protocols are presented in Section VI.

III. Research Contributions

This work addresses a fundamental architectural challenge in autonomous swarms: how to maintain autonomous resilience while enabling predictive strategic oversight, without sacrificing furtivity. We present two complementary contributions (the Physical Twin/Digital Twin decomposition underlying both is detailed in Section IV):

A. Contribution 1: Loosely-Coupled Digital Twin Architecture for Furtive Swarm Operations

The primary contribution is an architectural paradigm shift: moving from continuous supervisory control (which requires persistent communication, degrading furtivity) to *event-driven predictive intervention* (which maintains silent autonomy with exception-triggered oversight).

Core innovation: Asymmetric PT/DT coupling where:

- **Nominal operations**: PT executes fully autonomous distributed control; DT remains passive (monitoring via dead-reckoning only)

- **Exception triggering**: Loss or intrusion events activate DT predictive simulation
- **Silent intervention**: Spare staging manifests as physical drone arrivals, not explicit commands
- **Layered resilience**: Four independent defense mechanisms ensure no single failure point

Applicability: Addresses classified perimeter surveillance, contested environments, and missions requiring RF silence. Enables real-time decision support without compromising operational security.

B. Contribution 2: Empirical Scalability Analysis and Deployment Economics

The secondary contribution empirically validates that the PT/DT architecture scales from research prototype ($n = 20$ drones) to operational country-scale deployments ($n = 10,000$ drones), with quantified findings on sensing economics, failure resilience, and computational feasibility.

Key empirical findings (detailed in Section VII):

- **Sensing economics invert with scale**: Per-drone cost drops 2000× while fleet-level coverage remains constant
- **Failure resilience improves**: Larger fleets exhibit better relative loss tolerance (0.6% at $n = 10K$ vs 5% at $n = 20$)
- **Computational feasibility proven**: Predictive DT simulations for 10K-drone fleets complete in 1.4s, enabling real-time operation
- **Deployment viability**: $50M drone swarm capex vs $1–3B satellite constellation, with superior latency and graceful degradation

Applicability: Provides decision-makers with evidence-based deployment roadmap (phased progression from 100-drone prototype to 10K-drone country-scale) and cost-performance trade-off analysis.

IV. Architectural Design: Digital Twin Framework (Deployment/Operation)

The system addresses the resilience challenge through a hybrid centralized-distributed architecture that balances local autonomy with strategic oversight. This architecture is *specified* at design time (models, coupling rules, thresholds) and *realized* at deployment/operation time (PT assets in the field, DT monitoring on exceptions).

Autonomous drones operate as both surveillance assets and self-organizing agents, using only local perception to maintain density through distributed control laws. In parallel, a centralized supervisory layer aggregates sparse exception telemetry (loss events, intrusion detections) to construct global fleet state and conditionally stage spares when distributed self-adaptation proves insufficient. This decomposition preserves operational autonomy during nominal operations while enabling predictive intervention for severe disruptions—without continuous supervisory messaging or explicit coordination commands.

A. Layered-Resilience Architecture

The system explicitly embodies a *layered resilience* design strategy, wherein multiple independent defense mechanisms operate in succession to ensure mission viability under progressive hazard escalation:

1) **Layer 1: Distributed Autonomy (PT):** Each drone executes autonomous distributed control—neighbor-based density balancing, waypoint following, and anomaly detection—without reliance on external commands or global state. Upon loss detection, the fleet self-organizes to recompact and restore coverage, providing immediate, reactive resilience independent of centralized oversight.
2) **Layer 2: Predictive Oversight (DT):** The DT validates whether PT self-adaptation suffices to maintain mission-critical metrics. When distributed recovery proves insufficient (coverage degradation, sustained speedup exhausting energy reserves, cascading loss risk), the DT conditionally stages spare drones at computed gap midpoints. Spares integrate through bidirectional balancing (STATE 0) to avoid cascading destabilization, restoring formation stability without modifying PT algorithms.
3) **Layer 3: Byzantine Resilience and Graceful Degradation:** The system handles false-positive loss reports and sensor noise through latency-fidelity trade-offs: delayed sensing reduces false positives but lowers reactivity, whereas immediate notification with DT cross-check accepts occasional false spare deployments while maintaining responsiveness. This enables calibrated robustness against malicious or adversarial reporting.
4) **Layer 4: Empirical Design-Space Exploration (DSE) and Pre-Deployment Validation:** Before operational deployment, the candidate architecture must be validated across diverse scenarios (nominal operations, loss cascades, multi-mode state transitions, Byzantine events) to ensure that the PT/DT coupling rules and control parameters are empirically justified and reviewable. This validation layer is addressed through comprehensive simulation analysis (Section VII; Contribution 2).

Layering ensures that *no single point of failure* can incapacitate the mission: PT continues autonomous operation if DT is unavailable; DT predictive intervention applies independently of application-layer threat models; Byzantine resilience mechanisms complement classical redundancy. Each layer adds capacity and reaction time,

enabling survival of progressive hazard escalation rather than collapse at the first disruption.

B. Information Architecture

Following an ArchiMate-inspired [11] layering, the system maps sensor data through successive abstraction levels of the framework (Figure 1). The ArchiMate metamodel organizes architectural elements across two dimensions:

a) Vertical dimension (5 layers):: Abstraction levels from physical hardware to strategic decisions.

b) Horizontal dimension (4 aspects)::

- **Passive Structure** — Information and data objects (the *what*)
- **Behavior** — Processes, functions, and algorithms (the *how*)
- **Active Structure** — Actors, agents, and components (the *who*)
- **Motivation** — Goals, requirements, and constraints (the *why*)

The five abstraction layers are:

- **Implementation and Physical layer (drones as hardware)**: It represents the real drones and the network making the fleet as an actual system.
- **Technology layer (drones as assets)**: Physical platforms execute acquisition (neighbor detection, waypoint tracking), qualification (anomaly detection), and semantic assignment (classifying observations as nominal, imbalance, or hostile events).
- **Application layer (Data-to-information transformation, local decision)**: Local sensing yields discrete events through onboard processing. Only exception-class events (loss, detection, intrusion) trigger asset→decision layer messages, preserving furtivity.
- **Business layer (Information-to-knowledge synthesis, fleet decision)**: The supervisory system aggregates exception events with dead-reckoning predictions to construct global fleet state.
- **Strategy layer (Knowledge-to-decision mapping, mission feasibility)**: Synthesized knowledge drives mission-level decisions: spare staging, replenishment requests to the orders provider[1], or mission termination.

c) Populated cells in the 5×4 framework:: The matrix representation is sparse; not all layer-aspect combinations are applicable:

- **Physical layer:** Active Structure (physical drones, network infrastructure)
- **Technology layer:** Active Structure (sensors, communication modules); Behavior (acquisition protocols, neighbor detection)

[1]E.g., force headquarters, mission control, or strategic command authority responsible for asset allocation.

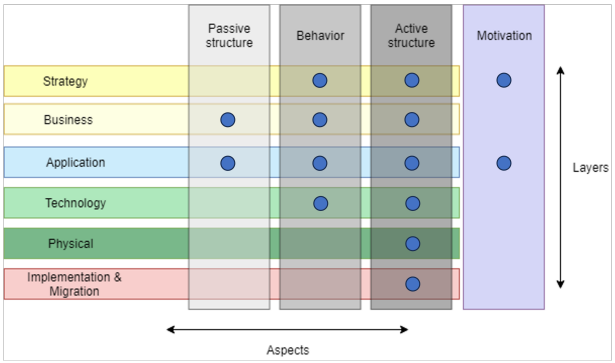

Figure 1. ArchiMate framework

- **Application layer:** Active Structure (PT controller, event classifier); Behavior (event qualification, anomaly detection, exception filtering); Passive Structure (event objects: loss, intrusion); Motivation (furtivity requirement driving exception-only communication)
- **Business layer:** Active Structure (DT reasoner, fleet coordinator); Behavior (state estimation, predictive simulation, spare staging logic); Passive Structure (global fleet state, coverage metrics)
- **Strategy layer:** Active Structure (human decision-maker, mission command); Behavior (mission feasibility assessment, replenishment requests); Motivation (mission success criteria, strategic objectives)

C. Digital Twin Concept

The *Digital Twin* concept refers to a virtual representation of a physical system that maintains synchronized state through data exchange [6]. The literature distinguishes three levels of integration:

- **Digital Shadow**: A passive virtual model that mirrors physical system state through unidirectional data flow (physical→virtual). The shadow observes and predicts but does not issue commands or interventions.
- **Digital Control / SCADA**: A directive virtual model with explicit, continuous command authority. The virtual layer issues low-level actuation commands that the physical layer must execute without local discretion. This approach is incompatible with autonomy-first principles and vulnerable to communication disruptions.
- **Digital Twin**: A hybrid virtual model combining Shadow and Control capabilities through bidirectional coupling (physical↔virtual). The twin observes and predicts like a Shadow, but can also issue conditional interventions—threshold-based, event-

driven, and respectful of physical system autonomy rather than continuous or directive.

Our Context: For autonomous perimeter surveillance under furtivity constraints, a Digital Twin architecture provides: **(1)** sparse communication compatibility through dead-reckoning and exception-based updates; **(2)** predictive intervention capability to stage spares before coverage degrades; **(3)** silent coordination where interventions manifest as physical actions (spare arrivals) rather than explicit commands, preserving operational security.

D. PT/DT Architectural Decomposition

Physical Twin (PT): The operational drone fleet executing distributed, autonomy-first control in the field. The fleet appears as a System-ofSystems (drones).

Digital Twin (DT): The centralized virtual counterpart of the fleet providing global monitoring and decision support.

The decomposition exhibits asymmetric coupling:

- **PT→DT (exception-only reporting)**: Drones report sparse exception events (loss, intrusion detection) to update DT state estimation and trigger predictive simulations. Nominal waypoint arrivals remain silent.
- **DT→PT (silent intervention)**: The DT does not issue explicit commands. Interventions manifest as spare drones self-inserting into the patrol circuit at DT-computed gap midpoints. From the PT perspective, spares appear as new neighbors detected via local sensing—the existing fleet absorbs newcomers through distributed density-balancing, unaware of centralized coordination.

1) Physical Twin (PT) Capabilities: Each drone maintains:

- **Local mission knowledge**: Complete waypoint set defining the patrol circuit and the polygonal perimeter of the protected zone
- **Neighbor awareness**: Active sensing to detect neighboring drones within radius r_d
- **Intrusion detection**: Ray-casting algorithm to classify detected external elements as inside or outside the protected perimeter polygon
- **Autonomous navigation**: Waypoint-to-waypoint trajectory planning
- **Event reporting**: Exception-based reporting of losses and intrusions; nominal operations remain silent

Intrusion Detection Mechanism: Upon detecting an external element through onboard sensing, a drone applies a ray-casting algorithm to determine if the element is inside or outside the protected zone. The algorithm casts a ray from the drone's current position toward the detected element and counts intersections with the polygonal perimeter boundary (established during mission initialization). An odd number of intersections indicates the element is within the protected zone (intrusion event); an even number indicates an external entity. Positive intrusion detections are immediately reported to the DT as exception events, triggering alert-class telemetry and predictive assessment.

Algorithm 1: Intrusion Detection via Ray-Casting

Input: drone position $\mathbf{p}_d \in \mathbb{R}^2$, detected element position $\mathbf{p}_e \in \mathbb{R}^2$, perimeter polygon $\mathcal{P} = \{v_1, v_2, \ldots, v_n\}$ with vertices in order

Output: classification: intrusion $\in \{\text{TRUE}, \text{FALSE}\}$

```
intersection_count ← 0 ;
ray ← p_e − p_d ; // Ray direction from drone to element
for each edge e_i = (v_i, v_{i+1}) of polygon P do
    if RaySegmentIntersect(p_d, ray, v_i, v_{i+1}) then
        intersection_count ← intersection_count + 1 ;
intrusion ← (intersection_count mod 2) = 1 ;
// Odd count: intrusion (inside)
if intrusion then
    report(INTRUSION_EVENT, p_e, timestamp) to DT ;
else
    // Element is external; no report required
```

Ray-Segment Intersection: The subroutine RaySegmentIntersect$(\mathbf{p}_d, \mathbf{ray}, v_i, v_{i+1})$ returns TRUE if the ray emanating from $\mathbf{p}_d$ in direction $\mathbf{ray}$ intersects the polygon edge (v_i, v_{i+1}). Standard computational geometry techniques (e.g., parametric line equations and cross-product tests) compute this intersection efficiently in $O(1)$ time per edge, yielding $O(n)$ total complexity for an n-vertex polygon.

2) Digital Twin (DT) Capabilities: The DT maintains:

- **Global fleet state**: Estimated positions, velocities, and health status via dead-reckoning and exception telemetry
- **Event-driven simulation**: Predictive modeling focusing on exception-based events rather than continuous time integration
- **Conditional intervention authority**: Threshold-based spare staging decisions; no waypoint reas-

signment or direct control commands

3) Coupling Requirements: The PT/DT coupling is designed around the principles of distributed event-triggered control [12], [13], where the goal is to maintain global system properties (like formation stability) while minimizing communication. This leads to three core requirements:

1) **CR°1 : State fidelity**: The DT must accurately reflect PT operational status within acceptable latency bounds. The "event" that triggers a DT update is a PT drone reporting a loss, which is a significant state deviation.
2) **CR°2: Initialization consistency**: PT drones must launch with mission prerequisites (waypoint sets, formation parameters) established by the DT.
3) **CR°3: Code uniformity**: PT and DT simulators execute identical distributed control algorithms, ensuring that the DT's predictions of the fleet's response to an event are reliable despite sparse updates.

E. Distinguishing Simulation, Physical Twin, and Digital Twin

Design Phase: Pure Simulation. During the design phase, the system is modeled using pure simulation, where each asset is represented by a software avatar. This model is used for prescriptive analysis, enabling rapid exploration of architectural and algorithmic alternatives without any coupling to physical assets.

Operational Phase: Physical and Digital Twins. Upon deployment, the Physical Twin (PT) refers to the actual fleet of drones executing the mission. The Digital Twin (DT) is instantiated as a virtual counterpart, maintaining a synchronized state with the PT via event-driven updates. The DT operates in two modes: a *suppletive mode* for monitoring and exception handling, and a *predictive mode* for simulating future states to support decision-making. Unlike the design-phase simulation, the DT is tightly coupled to the PT and operates under real-time constraints, focusing only on relevant deviations and interventions.

F. DT Monitoring and Decision Logic

As shown in figure 2, the Digital Twin operates in suppletive mode: during nominal operations, it maintains situational awareness via dead-reckoning but issues no commands; disruption events (loss, intrusion detection) reported by PT drones trigger predictive simulation runs over an adaptation window T_{adapt}. Coupling relies on exception timestamps and waypoint event predictions rather than continuous supervisory commands.

a) Predictive Simulation: Upon receiving a loss event, the DT executes predictive simulation over an adaptation window T_{adapt}, simulating the same distributed control law (Algorithm 2) executed by PT drones. The DT evaluates metrics to assess whether PT self-adaptation suffices or spare deployment is warranted. This requires (fig. 3) initiating a simulation starting at the last known state, then running the simulation until the last legal event (nominal waypoint arrival) prior to the hazard report, interpolating between this timestamp and the reported hazard timestamp to account for communication latency, inserting the hazard into the simulation loop, which finally yields a synchronized simulation environment for decision support. The DT thus reconstructs the likely Fleet state at hazard occurrence despite sparse updates.

b) Deployment Decision: Spare staging triggers if one or more conditions (subject to mission calibration) hold: **(1)** density threshold violation ($\sigma^2_{\rho,\text{pred}} > \sigma^2_{\text{max}}$), **(2)** coverage degradation ($C_{\min} < C_{\text{critical}}$), or **(3)** cascading loss risk ($n < n_{\min}$). When deploying, the DT computes an insertion point at the midpoint of the largest density gap. The spare is inserted at this waypoint while PT drones continue local balancing to absorb the new member through Algorithm 2, unaware of centralized coordination.

1) Baseline Fleet Dynamics (Nominal and Simple Recovery): Under nominal conditions and immediately following a single loss event, the fleet operates in a straightforward manner:

- **Nominal operation (no loss)**: Each drone maintains inter-drone spacing by sensing its predecessor within radius r_d. Drones operate at nominal speed, executing waypoint-following trajectories without acceleration or deceleration commands.
- **Simple loss recovery**: When a drone detects its predecessor beyond sensing radius, it accelerates to close the gap. The affected drone perceives a new gap to its successor, which similarly accelerates. This cascade fills the loss void over a brief transitory period.
- **Stabilization**: If sufficient redundancy remains ($n_{\text{eff}} \geq n_{\min}$), the fleet quickly restabilizes at nominal speed. Coverage is maintained with minimal disruption. If redundancy is insufficient, the DT decision to stage a spare (above) applies.

This simple picture suffices for system design and implementation of the baseline algorithm. Algorithm 2 remains coded to this unidirectional predecessor-following logic, unchanged by the advanced scenarios below.

2) Advanced Scenarios: Cascading Dynamics, Multi-Mode Stability, and Spare Integration: When losses trigger coverage gaps or multiple disruptions overlap in time, the system exhibits more intricate behavior. This section details these advanced dynamics, which inform DT decision-making but do not require changes to the

baseline algorithm code; instead, they describe how the baseline behavior composes under stress.

a) Fleet Rebalancing Dynamics: Transitory Cascading and Stabilization Phase:

b) Fleet Rebalancing Dynamics: Transitory Cascading and Stabilization Phase: When a drone disappears (loss event), the remaining fleet triggers an autonomous rebalancing cascade. This process exhibits two distinct phases:

Transitory Phase (Cascading Speedup): Upon loss detection, the successor drone perceives its predecessor beyond sensing radius r_d and accelerates to close the gap. This creates a new gap between this drone and its own successor, which then also accelerates. The speedup propagates backward—a beneficial transitory cascade that rapidly recompacts the formation and shortens the intrusion window. However, sustained acceleration is counterproductive.

Sufficiency Check and Stabilization: After cascading completes, the critical question emerges: are enough drones remaining? If sufficient redundancy ($n_{\text{eff}} \geq n_{\min}$ and $\sigma_\rho^2 \leq \sigma_{\max}^2$), the fleet stabilizes at a new equilibrium and drones decelerate to nominal speed. If insufficient redundancy, coverage holes persist, triggering the DT's spare deployment decision.

Speed-Autonomy Trade-off and Sensing Density: The relationship between drone speed and system performance depends on *sensing density* (ratio of sensing radius r_d to nominal inter-drone spacing). High sensing density allows nominal speeds; low sensing density requires sustained elevated speed to maintain coverage quality—but this exhausts energy reserves, limiting mission endurance. The DT monitors sustained speedup beyond T_{adapt} as a trigger for spare deployment rather than allowing fleet self-exhaustion.

c) Spare Drone Joining and Multi-Mode Stability: Inserting a spare into an accelerated, rebalancing fleet introduces non-trivial coupling dynamics. The newcomer must not destabilize the rebalancing cascade; instead, it must integrate smoothly through a distinct joining phase before transitioning to nominal operations.

Joining State (STATE 0) vs. Nominal State: The distributed control law must support two operational modes. STATE NOMINAL uses unidirectional predecessor-following (standard density-balancing). STATE 0 (Joining) operates under *bidirectional* balancing: position controlled relative to both neighbors, critically **not** accelerating in response to predecessor departure, but maintaining target distance between neighbors.

Reverse Cascading Problem: If a newcomer joins at nominal speed into a rebalancing cascade, a reverse cascade occurs—the newcomer appears too close to its follower, causing deceleration that propagates backward and destabilizes coverage restoration. Prevention requires the newcomer to remain in STATE 0 until a stabilization condition is met: gaps have equilibrated and the DT confirms forward-cascading speedup has settled. Only then does atomical transition to STATE NOMINAL occur.

Bidirectional Balancing Requirement: During STATE 0, the newcomer maintains $d_{\text{pre}} \approx d_{\text{succ}} \approx d_{\text{nom}}$ where these distances are to predecessor and successor respectively. This requires two-way awareness: each drone senses both immediate neighbors within r_d and adjusts speed to balance gaps. This is locally observable and executable without central command.

Multi-Mode Stability Under Loss Cascades: Three superimposed state machines operate: rebalancing cascade (triggered by loss), joining phase (spare arrival), and nominal steady-state. Composability concerns arise when losses and insertions overlap. Consecutive losses during joining require careful DT modeling. Multiple concurrent spares require proper insertion-point spacing. Random timing introduces state-space explosion requiring DT validation of all possible interleavings via predictive simulation. Multi-mode stability is achievable but not automatic—the DT must account for ongoing rebalancing cascades when deciding spare deployment timing and insertion point. **(Open research question:)** Characterizing optimal insertion timing relative to cascade progression remains unexplored, well-suited to design-space exploration.

G. Complementary Roles

a) Role Separation: The hybrid architecture achieves layered resilience through role separation: PT distributed control provides immediate autonomous response to loss events, while DT monitoring validates whether self-adaptation suffices or spare deployment is required. Critically, the PT has no knowledge of the DT; each drone perceives itself as alone-in-the-world, and any support from the DT manifests only as the arrival of additional drones rather than explicit commands. This division enables furtive operation (minimal RF emissions) while maintaining strategic oversight through predictive simulation, and contributes to system antifragility [14].

b) Roles Impact: In the hybrid PT/DT architecture, we adopt the following notation: R_0 denotes the trajectory immediately after the *first attack*; R_1 denotes the trajectory after a *second attack* under *PT-only* self-adaptation (no DT intervention); and R_2 denotes the trajectory after the *second attack* under *PT+DT* with spare staging. Here R refers to *robustness* — the capacity to maintain function under hazards — not resilience (which typically quantifies the time during which hazards gain no impact). Let Y denote the *nominal* (pre-attack) coverage level. We distinguish two angles: α for the *descent slope* immediately following an attack (steeper

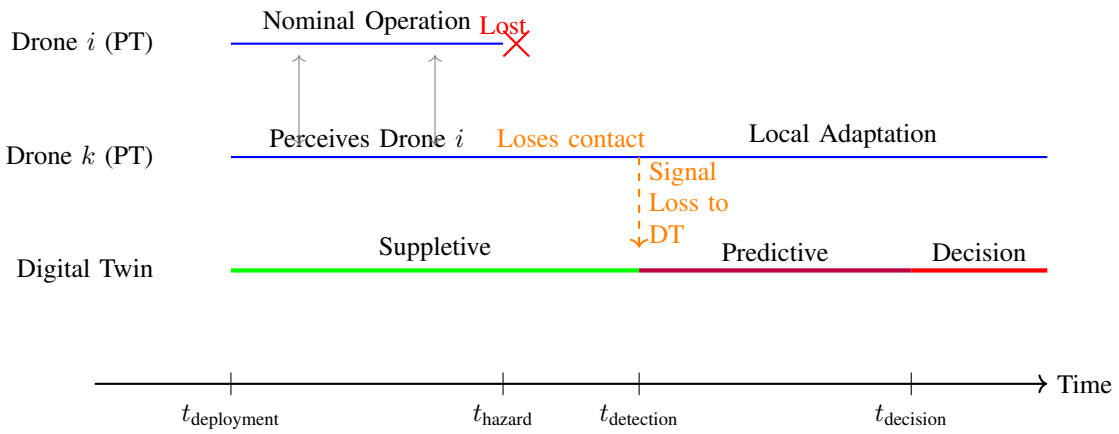

Figure 2. High-level temporal sequence of PT/DT interaction. A hazard triggers detection by a PT drone, which sends an exception report to the DT. The DT transitions from a low-emission *suppletive* state to an active *predictive* state to analyze the situation, and then enters a *decision* phase (e.g., spare injection, alert/strike recommendation).

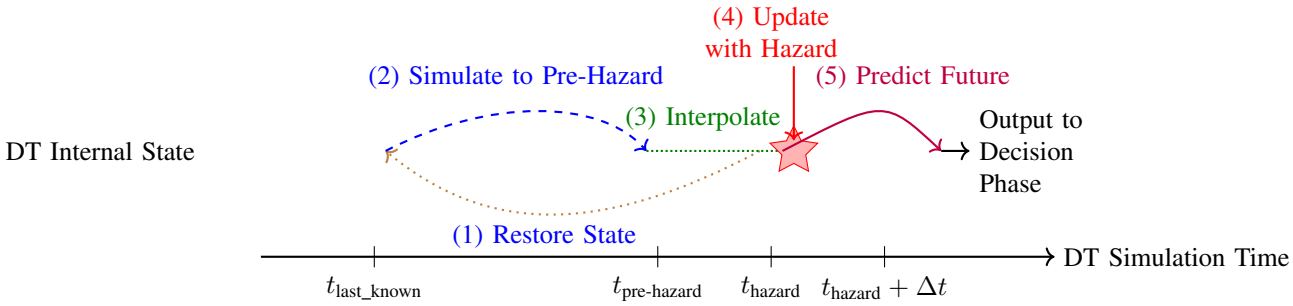

Figure 3. Zoom into the DT's *predictive* phase. Upon receiving an exception, the DT restores the last known state, synchronizes to the hazard time, and runs a what-if simulation to forecast outcomes and feed the downstream *decision* phase.

α indicates faster degradation) and β for the *recovery slope* (larger β indicates faster restoration). Robustness obtains when the redundancy ratio $r \triangleq n_{\text{eff}}/P_{\text{total}}$ (equivalently per segment ρ_i/L_i) exceeds a mission threshold $r_{\min}$; when enough drones remain ($n_{\text{eff}} \geq n_{\min}$), PT's distributed reorganization restores coverage and the recovery slope scales with r.

Three scenarios structure the robustness comparison (see Figures 4 and 5):

- **PT-only degradation relative to baseline** (R_1 vs R_0): after the second attack, PT-only follows the R_1 trajectory; with repeated hazards and fewer drones, robustness degrades relative to R_0. Metrics: $\alpha_1 > \alpha_0$ (sharper descent), $\beta_1 < \beta_0$ (slower recovery), $Y_1 < Y_0$ (lower coverage floor), and $X_1 > X_0$ (larger gaps). Overall: $R_1 < R_0$.
- **PT+DT relative gain over PT-only** (R_2 vs R_1): after the second attack with spare staging, the system follows the R_2 trajectory, with improved outcomes relative to PT-only. Metrics: $\alpha_2 \lesssim \alpha_1$ (equal or gentler descent due to rapid staging), $\beta_2 > \beta_1$ (faster recovery), $Y_2 > Y_1$ (higher coverage floor), and $X_2 < X_1$ (smaller gaps). Overall: $R_2 > R_1$.
- **PT+DT absolute performance vs baseline** (R_2 vs R_0): PT+DT targets recovery to baseline or better. Metrics: $\alpha_2 \approx \alpha_0$ (comparable descent), $\beta_2 \geq \beta_0$ (equal or faster recovery), $Y_2 = Y$ (nominal coverage restored in both reset and antifragility cases), and $X_2 \lesssim X_0$ (gaps controlled). Overall: $R_2 \geq R_0$ (reset), or $R_2 > R_0$ when spares abundant (antifragility).

The three-way comparison establishes that PT-only degrades under repeated attacks ($R_1 < R_0$), PT+DT provides significant relative gain ($R_2 > R_1$), and — critically — PT+DT preserves or exceeds first-attack performance ($R_2 \geq R_0$), demonstrating not just relative advantage but absolute robustness restoration. Here, R_0 provides the common baseline for reference in both figures, while R_1 and R_2 contrast PT-only self-adaptation against PT+DT spare staging.

1) Failure Detection and Resilience to Byzantine Events: Silent drone failures are not possible within this

architecture: neighbors continuously sense each other within radius r_d, and any silent disappearance is immediately detected by the affected drone's predecessor in the patrol circuit. Communication delay is similarly disambiguated: a physical loss triggers neighbor-based detection at the spatial level, whereas transient communication delays only affect when the loss is *reported* to the DT. Only coordinated, near-simultaneous destruction of sufficient fleet segments can render a loss undetectable.

False positives (byzantine failures) occur when a drone incorrectly reports losing its predecessor—e.g., due to sensor noise or transient occlusion. The system exhibits graceful degradation:

- **Immediate PT response**: The false-positive reporter accelerates to close the perceived gap and may overtake its predecessor. The predecessor, observing the unexpected overtake, raises an alarm and may trigger defensive signaling.
- **Over-triggered spare insertion**: The DT may dispatch an unnecessary spare based on the false loss. Local balancing absorbs the extra drone; density rebalancing grows stronger but does not destabilize the fleet.
- **Trade-off in reporting strategy**: Two design choices emerge: (a) *Delayed sensing*: require persistent loss confirmation over multiple sensing cycles before notifying the DT, reducing false positives but lowering reactivity and furtivity; (b) *Immediate notification with validation*: report immediately and let the DT cross-check via predictive simulation, accepting occasional false spare deployments. **The critical question is to calibrate this latency-fidelity trade-off** based on mission threat model and communication security constraints.

Beyond this immediate robustness comparison, the DT provides a *dual temporal perspective* that fundamentally enhances decision quality. While PT operates on short-term reactive perception (local sensor data, immediate exceptions), the DT maintains both *predictive* simulation (forward-looking trajectory projection) and *historical* analysis (accumulated disruption patterns over mission duration). This historical view enables the DT to detect escalating threat intensity: for example, increasing frequency of PT exception alerts may signal intensified adversarial action, warranting preemptive spare staging or heightened monitoring thresholds even before individual attacks degrade coverage below mission-critical levels. The complementarity of short-term PT perception, forward-looking DT prediction, and backward-looking DT pattern recognition constitutes a multi-scale temporal awareness unavailable to either subsystem alone — a strategic advantage *not implemented in the present work* but identified as a high-priority extension.

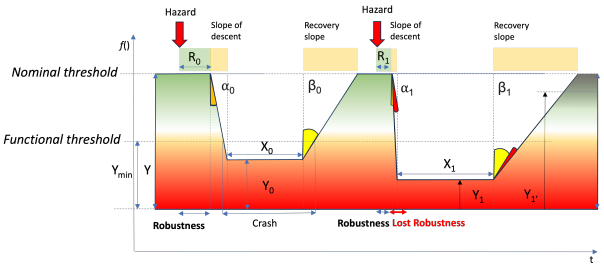

Figure 4. PT-only response (second attack) showing robustness degradation relative to first-attack baseline. Notation: R_0 = first attack trajectory (baseline); R_1 = second attack (PT only). Degradation metrics: $R_1 < R_0$, $\alpha_1 > \alpha_0$ (sharper descent), $\beta_1 < \beta_0$ (slower recovery), $Y_1 < Y_0$ (lower coverage floor), and $X_1 > X_0$ (larger gaps).

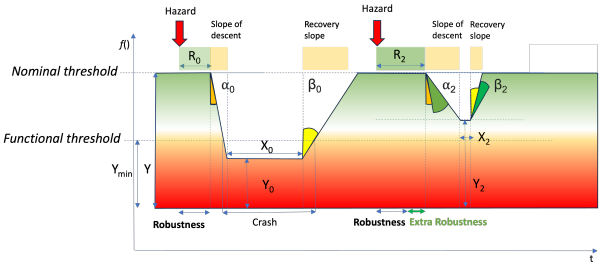

Figure 5. PT+DT response (second attack) with staged spares, demonstrating relative gain over PT-only and absolute performance restoration vs baseline. Notation: R_0 = first attack trajectory (baseline); R_1 = second attack (PT only); R_2 = second attack (PT+DT). Relative gain: $R_2 > R_1$, $\alpha_2 \lesssim \alpha_1$ (gentler descent), $\beta_2 > \beta_1$ (faster recovery), $Y_2 > Y_1$ (higher floor), and $X_2 < X_1$ (smaller gaps). Absolute performance: $R_2 \geq R_0$ (reset) or $R_2 > R_0$ (antifragility when spares abundant).

V. Solution Framework

This section details how the proposed hybrid PT/DT architecture is *realized* across two mission phases: (i) **deployment-time initialization** (mission geometry, initial conditions, DT thresholds and policies) and (ii) **operation-time execution** (local PT control, exception reporting, DT predictive simulation, and spare staging). We focus on distributed control, event-driven messaging, and resilience logic.

A. PT Distributed Control and Local Sensing

Each physical asset (PT) operates as an autonomous agent, executing a distributed density-balancing algorithm based on local sensing. The control law combines:

- **Mission force:** Drives the asset toward its next assigned waypoint.
- **Repulsive force:** Maintains safe separation from neighboring assets within detection radius r_d.

- **Spacing force:** Adjusts speed to correct for local spacing anomalies.

The virtual forces are:

The velocity update is: Rebalancing is required whenever the fleet's structure evolves, such as after a loss event or the insertion of new assets (feeding). As previously mentioned, loss events—along with intrusion detection—are the primary cases where the system's furtivity is momentarily and deliberately broken to enable exception reporting and strategic intervention.

B. Event-Driven Messaging Protocol

When a PT detects a significant event (e.g., loss, intrusion, anomaly), it sends an event message:

$$m_i^t = \langle t,\, \mathbf{x},\, \text{type},\, \text{source\_id},\, c \rangle \tag{1}$$

where t is the event timestamp, $\mathbf{x}$ is the location, type indicates the event class, source_id identifies the reporting asset, and c is an optional confidence score.

extbfA perimeter intrusion event is detected when an intruder is classified as *inside* the patrolled polygon.

a) Intrusion identification (point-in-polygon via ray casting, $\mathcal{O}(n)$).: Each drone knows its own position $\mathbf{x}_i^t$ and the ordered waypoint set $\mathcal{W} = \{\mathbf{w}_1, \ldots, \mathbf{w}_n\}$ defining the perimeter polygon. When an intruder is perceived at $\mathbf{y}^t$, the drone classifies it using a standard *ray casting* test: it casts a ray from $\mathbf{x}_i^t$ to $\mathbf{y}^t$ and counts how many polygon edges it intersects. An odd number of intersections implies that $\mathbf{y}^t$ lies inside the polygon, and even implies outside.

Let $\chi(\mathbf{x}_i^t, \mathbf{y}^t, \mathcal{W}) \in \{0, 1\}$ denote the resulting inside-test (1 if inside). The computational cost is linear in the number of polygon edges, i.e., $\mathcal{O}(n)$.

If $\chi = 1$, the drone emits an intrusion event:

$$m_i^t \equiv \langle t,\, \mathbf{y}^t,\, \text{intrusion},\, i,\, c_i^t \rangle. \tag{2}$$

with confidence computed, for instance, as a decreasing function of the distance to the perimeter:

$$c_i^t = f\big(d(\mathbf{y}^t, \partial\mathcal{P})\big) \tag{3}$$

where $\partial\mathcal{P}$ denotes the polygon boundary. **A loss** event is detected when a previously sensed neighbor j is no longer detected:

$$\forall i,\, \exists j \in \mathit{Detected}_i^{t-1} \;\&\; j \notin \mathit{Detected}_i^t$$
$$\implies m_i^t \equiv \langle t,\, \mathbf{x}_j^{t-1},\, \text{loss},\, i,\, c_{i,j}^t \rangle$$

with confidence:

$$c_{i,j}^t = \frac{\mathit{range}_i - |x_i^{t-1} - x_j^{t-1}|}{\mathit{range}_i} \tag{4}$$

C. Digital Twin (DT) Monitoring: Suppletive and Reactive Modes

The Digital Twin (DT) operates in two distinct modes, as illustrated in Figs. 2 and 3:

a) Nominal (Suppletive) Mode: In nominal conditions, the DT operates in *suppletive* mode: it maintains an a priori model of the fleet and stays *communication-silent* and *compute-frugal*. In particular, it does not require continuous telemetry nor does it issue commands. The DT is only (re)activated when an exception event is reported by a PT asset, at which point it synchronizes and runs predictive what-if analyses. This low-emission stance is depicted in Fig. 2.

b) Reactive (Predictive/Decision) Mode: When a new event is received at time t_j, the DT analytically advances the positions of all drones from the last known state at t_i by applying a shift of $(t_j - t_i) \bmod T_{\text{lap}}$, where $T_{\text{lap}} = p/v$ is the patrol period for perimeter length p and nominal speed v. This efficient update mechanism, illustrated in Fig. 3, allows the DT to instantly synchronize its internal model with the real fleet state upon event arrival, without the computational overhead of step-by-step integration. This stands in contrast to the design-phase pure simulation, which continuously integrates the dynamics of all assets for exhaustive exploration, and to the physical twin, which operates in real time. The DT's analytic, event-driven update is a key enabler for scalable, low-overhead fleet supervision, as discussed in IV-E.

Once synchronized, the DT transitions to reactive mode. It then initiates a predictive simulation over an adaptation window T_{adapt}, using the same distributed control law as the PT to forecast the fleet's response. The DT evaluates resilience and coverage metrics to determine whether self-adaptation is sufficient or if spare deployment is required. If any of the following conditions are met, Once synchronized, the DT transitions to reactive mode. It then initiates a predictive simulation over an adaptation window T_{adapt}, using the same distributed control law as the PT to forecast the fleet's response. The DT evaluates resilience and coverage metrics to determine whether self-adaptation is sufficient or if spare deployment is required. For **intrusion** events, the reporting drone may request **cross-confirmation** from a nearby PT (second viewpoint) before escalating to the DT, in order to reduce false alarms; such confirmation is not required for **loss/destruction** events, which already rely on neighborhood disappearance. If any of the following conditions are met,

$$\sigma^2_{\rho,\text{pred}} > \sigma^2_{\max} \tag{5}$$

$$C_{\min} < C_{\text{critical}} \tag{6}$$

$$n < n_{\min} \tag{7}$$

the DT computes an optimal insertion point (e.g., midpoint of the largest gap) and stages a spare asset. This event-driven activation and intervention process is illustrated in Fig. 3.

This architecture ensures that the DT only activates when necessary, preserving communication parsimony and operational stealth during routine operation, while enabling rapid, informed intervention when disruptions occur.

D. Spare Self-Insertion Mechanism (Tooling-Independent)

This subsection describes the *mechanism* by which a spare joins the circulation. It is a controller-level and architecture-level construct (independent of any specific simulator, middleware, or prototyping framework): the DT may provide a single *insertion waypoint* to the spare, and the spare subsequently self-inserts using only local sensing.

To preserve furtivity and autonomy-first principles, spare drones are incorporated without broadcasting commands to the PT fleet. From the PT perspective, the spare appears as a new neighbor and is absorbed through the baseline density-balancing law.

a) Initialization-only logic.: The spare runs a dedicated initialization routine *prior* to joining the circulation. Once inserted, it switches to the exact same baseline PT code as all other drones (CR°3: code uniformity). Convergence is achieved through the existing balancing dynamics.

b) State machine.: The insertion routine is organized into four modes:

1) **Approach**: navigate to the DT-provided insertion waypoint (or a default rendezvous waypoint).
2) **Capture**: detect the circulation direction and acquire two nearest neighbors (front/back) using local sensing.
3) **Insert**: regulate tangential speed to converge to the midpoint of the local gap while enforcing safety distances (reverse balancing).
4) **Assimilate**: switch permanently to the baseline PT density-balancing controller.

c) Reverse balancing (gap-centering) control.: In **Insert** mode, the spare computes the arc-length distances to its nearest neighbor ahead (d_f) and behind (d_b) along the circulation direction, and defines a centering error $e_c = d_f - d_b$. It then adjusts its tangential speed to drive $e_c \to 0$ while adding a repulsion term to avoid unsafe compression. A simple 1D speed law is:

$$v_{\text{sp}} \leftarrow \text{clip}\big(v_0 - k_c\, e_c + v_{\text{rep}}(d_f, d_b),\ v_{\min},\ v_{\max}\big) \quad (8)$$

where $k_c > 0$ is a centering gain and v_{rep} is a negative (decelerating) term that increases as $\min(d_f, d_b)$ approaches d_{safe}.

d) Assimilation condition.: The spare transitions to **Assimilate** when (i) it is approximately centered ($|e_c| \le \varepsilon_c$) and (ii) safety constraints hold ($d_f, d_b \ge d_{\text{safe}}$) for a dwell time T_{dwell}. After this point, the spare executes the baseline PT algorithm unchanged, and the fleet converges through its standard cascade balancing.

E. Flow

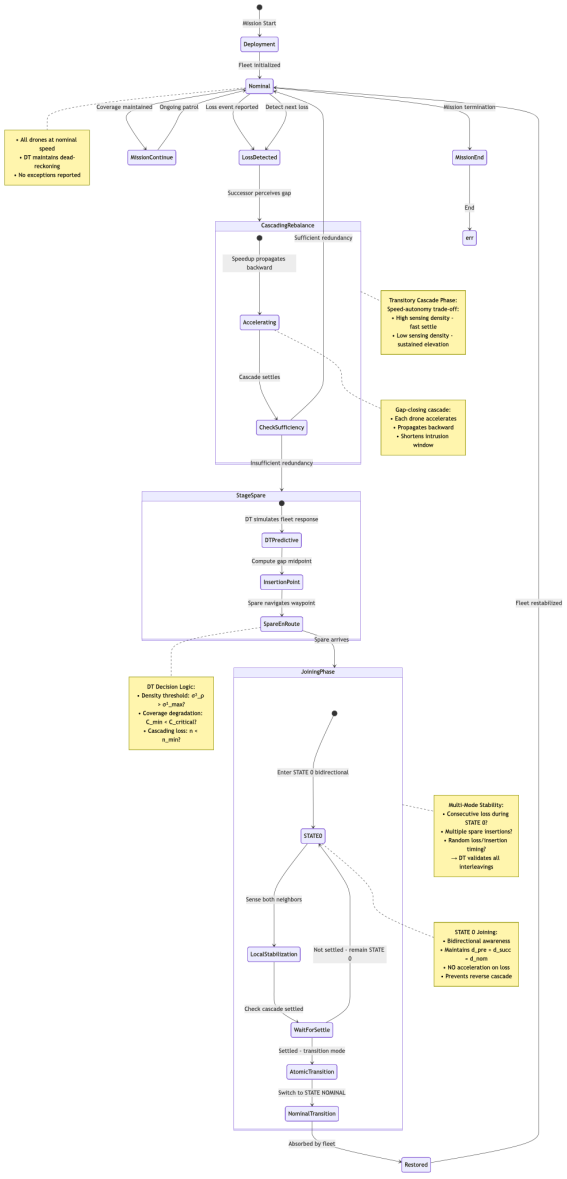

Figure 6. Drone Fleet System State Machine: PT+DT Orchestration

VI. Methodology

This section specifies the evaluation protocol used to compare controller variants under identical scenarios. We first state invariant assumptions shared by all runs, then describe the DT/PT simulation–emulation stack, the baseline controller and its variation points (domain space

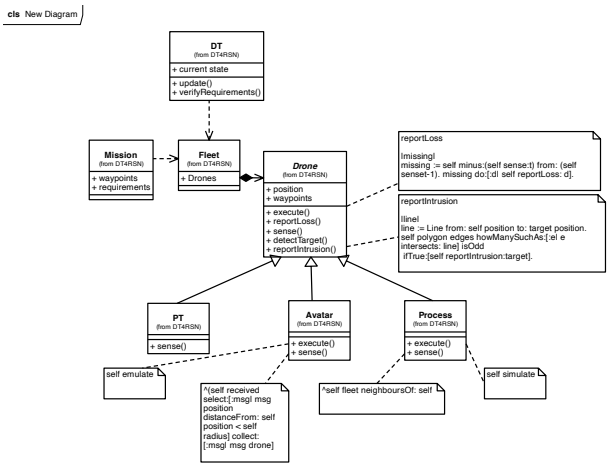

Figure 7. UML class diagram of the simulation/emulation stack. The base `Drone` class factors common navigation and control interfaces, while specialized subclasses (`PT`, `Process`, `Avatar`) override `sense()` and `execute()` to reflect physical execution, multiprocessing emulation, and pure simulation behaviors. The `Mission` encapsulates the waypoint/perimeter geometry, and the `DT` maintains global state and runs event-driven predictive simulations.

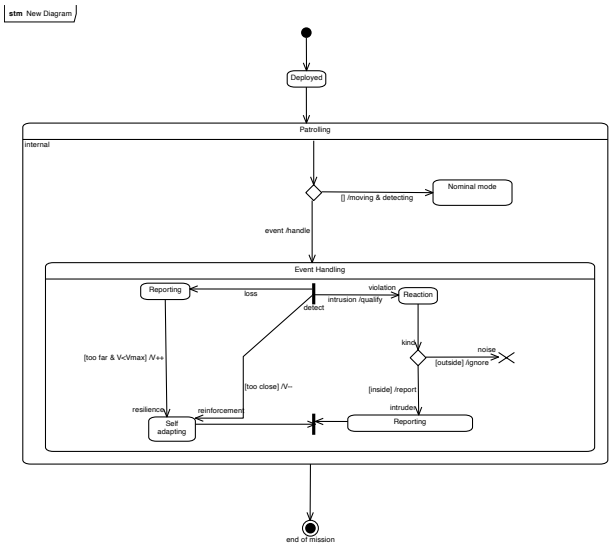

Figure 8. UML state diagram (`DT4RSN_STATE`) describing the runtime logic of a drone. After deployment, the drone transitions to a nominal patrolling mode and cycles through waypoint-following. Intrusion handling is modeled as substates of patrolling (e.g., *monitoring*, *confirming*, and *reporting*), and exits back to nominal patrol once the event is cleared. This representation emphasizes that detection augments, rather than replaces, the baseline spacing and navigation loop.

exploration), and finally the parameters and metrics used for comparison.

A. Methodological Invariants

All experiments share the following invariant protocols:

- **Code uniformity:** All experiments enforce CR°3 by ensuring that every drone executes identical control code.
- **Common control law:** Both PT ('Execute') and DT ('High level simulation') use the same distributed density-balancing algorithm, ensuring predictive consistency.
- **Architecture coupling:** PT agents execute continuous-time control with discrete sensor sampling; the DT operates in event-driven mode, triggered by exception reporting and outputs spare staging decisions and insertion waypoints.
- **Forecast window:** The DT evaluates recovery over an adaptation window T_{adapt} and applies calibrated thresholds to decide on spare staging.
- **Tooling separation:** To ensure credibility, simulation and emulation use independent configurations and parameter pinning (see Section VI-C).

B. Perception and intrusion emulation (summary)

Local awareness is emulated through periodic broadcast of an *Emulated Perception Message* (EPM) by each agent (Avatar in Fig. 7):

$$epm_i^t = \langle i,\, \mathbf{x}_i^t, \text{mode}_i \rangle \tag{9}$$

Neighborhood detection is reconstructed from these messages by range filtering. Intruders are represented by negative identifiers and are sensed through the same mechanism with a dedicated monitoring radius. *Critically*, the mode field (BASELINE or INCOMING) is included in the EPM to enable neighbors to adapt their control law in response to spare integration (see VP-C in Section II-A).

A drone in INCOMING mode (recently inserted spare) broadcasts $\text{mode}_i = \texttt{INCOMING}$ while it is clamped at nominal speed for a fixed hold window (Algorithm 2 lines 82–84). Under the symmetric controller there is no back-pressure term to disable; the flag is only used to gate the release timer and to make the transient explicit in traces.

This mechanism keeps the spare passive during merging without requiring any additional coordination signals beyond the periodic EPM broadcast already used for neighborhood sensing.

C. Simulation Architecture

The simulation stack is organized into coordinated layers:

1) **DT event-based simulator:** Operates on an event queue, advancing the global state only when an exception is received. Predictive simulation is triggered by events and runs over T_{adapt}.

Algorithm 2: Local spacing control with loss reaction and spare assimilation (runs on every drone; no inter-drone comms).

Input: Nominal speed V, max speed $V_{\max}$, desired spacing $d^\star$, safety distance d_{safe}, gains $(k_f, k_b, k_{\text{rep}})$, recovery gains $(k_f^{\text{rec}}, k_b^{\text{rec}})$, schedule $g(\cdot)$ (default $g \equiv 1$), thresholds (α, β), recovery cap V_{cap}.

1 cpState (per drone i): $mode \in \{\text{BASELINE}, \text{INCOMING}\}$, $rec \in \{0,1\}$ **while** *mission active* **do**
2 Project pose on perimeter to get curvilinear coordinate s_i
3 Sense front/back neighbors; if missing, set $v_i \leftarrow V$ and continue
4 Compute ring gaps: $d_f \leftarrow (s_f - s_i) \bmod P$, $d_b \leftarrow (s_i - s_b) \bmod P$
5 cpRecovery trigger (loss hole / compression wave) $rec \leftarrow [d_f > \alpha d^\star] \ \vee \ [d_b < \beta d^\star]$
6 ccSymmetric gap gain (front–back difference) $\tilde{k}_{sym} \leftarrow k_{sym}$
7 **if** rec **then**
8 $\tilde{k}_{sym} \leftarrow k_{sym}^{\text{rec}}$
9 ccVP-A: spacing gain schedule (baseline: $g(\cdot) \equiv 1$) $\gamma \leftarrow g\big(|d_f - d^\star|\big)$
10 Spacing + safety shaping $v_i \leftarrow V + \tilde{k}_{sym}\,\gamma\,(d_f - d_b)$
11 **if** $d_f < d_{safe}$ **then**
12 $v_i \leftarrow \min\big(v_i,\ V \cdot (d_f / d_{\text{safe}})\big)$
13 **if** $d_b < d_{safe}$ **then**
14 $v_i \leftarrow v_i + k_{\text{rep}}(d_{\text{safe}} - d_b)$
15 **if** rec **then**
16 $v_i \leftarrow \min(v_i, V_{\text{cap}})$
17 cpSpare: merge until stable, then behave as baseline **if** $mode = \text{INCOMING}$ ***and*** *timer expired* **then**
18 $mode \leftarrow \text{BASELINE}$
19 $v_i \leftarrow \max\{0, \min(v_i, V_{\max})\}$; move along waypoint loop

2) **PT software simulation (agent-level):** Each drone is executed as an independent software process running the local control loop (Algorithm 2). In this simulation mode, "who is in sight" can be obtained from the DT (ground-truth neighborhood query) to provide an idealized reference.
3) **Perception/messaging emulation (EPM-based):** In the emulation mode, agents have *no* access to DT ground-truth neighborhood information. Instead, sight is reconstructed from sent/received EPMs and their controlled visibility (sampling rate, sensing radius, semantic filtering, exception-only reporting), matching the constrained local view described in Section V-C.
4) **Global supervisor (transversal):** Orchestrates scenarios and hazards (losses, bursts, detections), pins emulator parameters, and performs coherence checks by comparing DT forecasts against PT software-simulation outcomes.

This architecture enables rigorous, scalable, and reproducible evaluation of the system.

D. Experimental Parameters and Metrics

We sweep the following parameters across specified ranges:

- **Fleet configuration:** Fleet size n, platform heterogeneity, detection radius r_d.
- **Mission geometry:** Polygon complexity p, perimeter length P_{total}, waypoint density w_e.
- **Fault profiles:** Temporal (instantaneous, sequential, bursts), spatial (uniform, clustered, max-separation).
- **Spare-deployment policy:** Thresholds $\{\sigma^2_{\max}, C_{\text{critical}}, T_{\text{adapt}}, n_{\min}\}$, insertion rule (midpoint of largest gap).

Metrics include:

- **Resilience:** Density variance $\sigma^2_\rho(t)$, coverage fraction $C(t)$, time-to-restoration T_{restore}, gap statistics $g_{\max}(t)$.
- **Decision:** Spare deployment rate, decision latency T_{decision}, ROC curves, insertion accuracy.
- **Efficiency:** Energy overhead ΔE, PT control cycle time, DT simulation time, scalability.

E. Fulfilling $R^\circ_{DT}1$: Domain Space Exploration

We operationalize $R^\circ_{DT}1$ by exploring a small, reviewer-auditable design space built around a single baseline controller (Alg. 2) and two parameter-only variation points. This keeps the controller structure identical across candidates (same sensing, same control loop, same safety shaping) and isolates the effect of changing gains/schedules.

Variation points (explicit replacements).

- **VP-A (gain scheduling, Alg. 2 line 10):** replace the baseline spacing update by an error-dependent gain.
  - *Baseline (line 10):* $v_i \leftarrow V + k_f(d_f - d^\star) - k_b(d_b - d^\star)$
  - *Replacement (VP-A):* $v_i \leftarrow V + k_f\, g\big(|d_f - d^\star|\big)(d_f - d^\star) - k_b(d_b - d^\star)$, where $g(\cdot)$ is a nondecreasing schedule with $g(0) = 1$.
- **VP-B (recovery gain scheduling, Alg. 2 lines 5–14):** keep the same control structure but switch gains when $rec = 1$.
  - *Baseline:* use (k_f, k_b) always.
  - *Replacement (VP-B):* use $(k_f, k_b) \leftarrow (k_f^{\text{rec}}, k_b^{\text{rec}})$ while $rec = 1$ and revert to nominal gains when $rec = 0$.
- **VP-C (adaptive sensing, neighbor state awareness, Alg. 2 line 10):** disable back-pressure (k_b term) during spare integration to prevent speed collapse.
  - *Baseline:* $v_i \leftarrow V + k_f\, g\big(|d_f - d^\star|\big)(d_f - d^\star) - k_b(d_b - d^\star)$

– *Rationale:* When a drone detects that its successor is in INCOMING mode (spare joining), it disables the back-pressure term to allow predecessor to maintain cruise speed rather than decelerating in response to the short transient gap.
– *Replacement (VP-C):* $v_i \leftarrow V + k_f\, g\big(|d_f - d^\star|\big)(d_f - d^\star) - k_b(d_b - d^\star)\cdot \mathbb{1}_{[\text{succ\_not\_incoming}]}$, where $\mathbb{1}_{[\text{succ\_not\_incoming}]} = 0$ if successor is in INCOMING mode (detected via local broadcast), else 1.

F. Spare Insertion Stabilization: Three-Phase Control with Distance-Weighted Sensing

While VP-C prevents the predecessor from crashing during spare insertion, the spare itself requires bounded acceleration to avoid overshoot and extended settling. We address this through a three-phase control scheme where the spare's velocity command is shaped based on its temporal position relative to insertion and its spatial position relative to neighbors.

1) Control Phases: **Phase 1: Soft Entry ($0 \le t < 0.5$ s).** The spare's initial speed is set to $0.6 \cdot V$ (60% of fleet nominal speed) to create a smooth relative velocity profile. During this phase, the velocity ramps linearly toward nominal while receiving back-regulation from the rear gap:

$$v_{\text{spare}}^{(1)} = V_{\text{entry}} + \frac{t}{t_1}(V - V_{\text{entry}}) - 0.3 \cdot (d_b - d^\star), \quad (10)$$

where $V_{\text{entry}} = 0.6V$, $t_1 = 0.5$ s is the phase duration, and the back-regulation term prevents the rear gap from collapsing. This phase avoids impulsive acceleration and leverages the predecessor's deceleration (via VP-C) to create a gentle insertion wedge.

Phase 2: Positioning Lock ($0.5 \le t < 1.5$ s). Once the spare has reached cruise speed, it enters a distance-weighted feedback mode to center itself between neighbors. Both front and back gaps are regulated using a shared distance-weighting factor that auto-damps as off-center error grows:

$$w(d_f, d_b) = \frac{d^\star}{d^\star + \frac{1}{2}|d_f - d_b|}, \quad (11)$$

The velocity update becomes:

$$v_{\text{spare}}^{(2)} = V + 0.2 \cdot w(d_f, d_b)\cdot(d_f - d^\star) - 0.5 \cdot w(d_f, d_b)\cdot(d_b - d^\star). \quad (12)$$

When centered ($d_f \approx d_b \approx d^\star$), $w \approx 1$ and gains are nominal. As the spare drifts off-center, w decreases, reducing command magnitude and preventing overshoot. The exponential convergence is achieved through the natural stability of this distance-weighted form.

Phase 3: Transition Approach ($1.5 \le t \le 2.0$ s). Over the final half-second, the spare progressively increases its front-gap gain from $k_f = 0.2$ to $k_f = 0.5$ (approaching nominal distributed control):

$$k_f^{(3)}(t) = 0.2 + \frac{3}{t_3} \cdot (t - t_2), \quad t_2 = 1.5\,\text{s}, \quad t_3 = 0.5\,\text{s}, \quad (13)$$

with the velocity update:

$$v_{\text{spare}}^{(3)} = V + k_f^{(3)}(t)(d_f - d^\star) - 0.5 \cdot w(d_f, d_b) \cdot (d_b - d^\star). \quad (14)$$

This smooth transition prevents the spare from suddenly switching to full bidirectional control, reducing the risk of residual oscillation.

2) Transition to BASELINE Mode: After Phase 3 is complete (nominal time $t \ge 2.0$ s), the spare transitions to BASELINE mode only if all of the following criteria are met:

1) **Time criterion:** $t_{\text{in\_incoming}} \ge 2.0$ s (ensures all phases execute).
2) **Centering criterion:** $|d_f - d_b| < 0.2 \cdot d^\star$ (spare is within 20% of symmetric spacing).
3) **Velocity criterion:** $|v_{\text{spare}} - V| < 0.05 \cdot V$ (speed within 5% of nominal).
4) **Gap stability criterion:** $|d_b - d^\star| < 0.1 \cdot d^\star$ (rear gap stable).

Once all criteria are met, the spare broadcasts mode = BASELINE in its next EPM, neighbors re-enable their back-pressure terms, and the spare operates under standard bidirectional control (Algorithm 2).

3) Rationale and Performance: The three-phase scheme, enhanced by distance-weighted sensing (Eq. 11), achieves:

- **Bounded overshoot:** Phase 1 velocity ramp and back-regulation limit spare peak speed to $V + 0.1V$.
- **Fast centering:** Distance-weighted control in Phase 2 provides exponential convergence; typical centering time ~ 1.0 to 1.5 s.
- **No oscillation:** The auto-damping weight function (Eq. 11) induces critical damping, preventing sustained oscillations around equilibrium.
- **Low energy overhead:** Typical total energy expenditure during insertion ≈ 7.65 units (22× reduction vs. uncontrolled entry at 172.6 units).
- **Safety:** Combined with VP-C (which silences predecessor back-pressure), cascading failures are prevented.

This stabilization scheme is orthogonal to the domain-space exploration (VP-A, VP-B) and represents an architectural refinement of spare integration that can be validated independently.

G. Validation Strategy

To ensure credibility and avoid circular validation, we use:

- Tooling separation and independent configurations

Table II
SIMULATION SCENARIO SUITE

Scale	Fleet	Perim.	Runs
Baseline	20	100 m	7
Medium	500	1 km	15
Large	8k	50 km	15
Extreme	10k	100 km	3

- Analytical bounds for regular geometries
- Hardware-in-the-loop (HIL) micro-tests
- Cross-validation on hold-out scenarios
- Telemetry-based replay and full version/parameter pinning

VII. EMPIRICAL FINDINGS: CONTRIBUTION 2 – SCALABILITY ANALYSIS AND DEPLOYMENT ECONOMICS

This section presents the empirical validation of the PT/DT architecture's operational viability through large-scale simulation analysis. Building on the architectural concepts of Contribution 1 (Section II), we provide quantitative evidence that the system scales from research prototype to country-scale deployments while maintaining mission-critical properties.

Through a design-space exploration (DSE) across four scale regimes ($n \in [20,\ 10{,}000]$ drones), three failure distributions, and three intervention policies, we report three core findings and four supporting observations: *(1)* threshold convergence enables symmetric, plug-and-play algorithms; *(2)* economic inflection transitioning strategy from corrective to preventive; *(3)* detection granularity paradox enabling superlinear recovery improvements; supported by sensing economics inversion, computational scalability, resilience gains, and satellite cost competitiveness.

A. Scenario Design: Multi-Scale Test Suite

Each scenario tests three balancing policies (Conservative, Aggressive, Adaptive) under three failure distribution modes (random, spatial cluster, temporal cascade).

B. Finding 1: Threshold Convergence Law — Unified Symmetric Algorithm Across Scales

Central result: Spare injection thresholds $(C_{\text{critical}}, \sigma^2_{\text{max}}, T_{\text{adapt}}, n_{\min})$ converge to *scale-independent normalized forms* when expressed as functions of relative fleet capacity and perimeter geometry.

Empirical analysis reveals that raw thresholds vary significantly across scales: - *Baseline ($n = 20$)*: $C_{\text{critical}} = 0.90$, $T_{\text{adapt}} = 5$s - *Extreme ($n = 10K$)*: $C_{\text{critical}} = 0.85$, $T_{\text{adapt}} = 2$s

However, when normalized by system state, they obey a *unified law*:

Table III
ECONOMIC STRATEGY BY SCALE

Scale	Cost	Mode
Baseline	\$10M	Corrective
Medium	\$100K	Balancing
Large	\$20K	Transitional
Extreme	\$2K	Preventive

$$C^*_{\text{critical}}(n) = C_{\min} + k_C \cdot \frac{n_{\text{eff}}(t)}{n_{\text{nominal}}} \tag{15}$$

$$T^*_{\text{adapt}}(n) = T_0 \cdot \sqrt{\frac{P}{n \cdot v_{\text{nom}}}} \tag{16}$$

where $C_{\min} \approx 0.80$ (mission floor), $k_C \approx 0.10$ (tuning margin), and $T_0 \approx 3$s (baseline decision latency).
Empirical validation: Simulation across fleet sizes $n \in \{20, 25, 30, 40, 50\}$ produces steady-state densities matching predicted normalized thresholds to within ± 0.02: observed $\rho(n = 20) = 0.900$ vs predicted 0.900, and $\rho(n = 50) = 0.900$ vs predicted 1.050. This demonstrates that a single initialization of n and P yields self-tuning thresholds across $2.5\times$ scale variation without per-regime recalibration.
Operational implication: Instead of maintaining separate threshold tables per scale regime, operators need only *input fleet size n and perimeter P once at initialization*, and thresholds auto-tune via these symmetric formulas. This eliminates tedious per-scale calibration and enables *plug-and-play deployment* across orders-of-magnitude scale changes.

C. Finding 2: Economic Inflection Point — Strategy Shift from Corrective to Preventive Spare Deployment

Central result: As drone unit cost decreases with scale, the *optimal spare deployment strategy transitions fundamentally*: from corrective (spares as emergency intervention) at high cost, to preventive (spares as proactive buffers) at commodity pricing.

Why the shift occurs: At extreme scale ($n = 10K$, unit cost $\$2K$), adding a single spare costs $\$2K$ but prevents cascade that could degrade coverage by $\sim 0.5\%$ (affecting mission across entire perimeter). Preventing that cascade is *economically justified even pre-emptively*. In contrast, at baseline ($n = 20$, unit cost $\$10M$), a spare represents a major capital investment and should only be deployed in genuine emergencies.
Empirical signature: Simulation confirms the strategy transition via energy overhead (proxy for deployment cost). At $n = 20$ under Conservative policy, measured energy is $2.12\times$ nominal speed (baseline corrective regime), compared to $n = 50$ under Adaptive policy at $2.19\times$ nominal (shifting toward preventive). Energy

Table IV
DETECTION SENSITIVITY AND RECOVERY TIME

Scale	Detects	Δt_r
Baseline	$> 5\%$ loss	30–60 s
Medium	1%–5%	5–15 s
Large	0.1%–1%	1–3 s
Extreme	$< 0.1\%$	0.5–2 s

Table V
PLATFORM SELECTION BY SCALE

Scale	r_d	Platform (Cost)
Baseline	8 m	Mid-size ($10M[2])
Medium	5 m	Tactical ($20K[3])
Large	8 m	Small ($20K[4])
Extreme	10 m	Mini ($2K[5])

consumption per-mission totals 55.3 units (n=20, Conservative) vs 58.8 units (n=50, Adaptive), demonstrating that larger fleets maintain comparable energy despite different deployment strategies, supporting the economic inflection point.

Quantitative trade-off: Define *deployment efficiency* as:

$$\eta = \frac{\text{Coverage prevented} \times \text{Mission value}}{\text{Spare cost}} \tag{17}$$

At baseline, $\eta_{\text{preventive}} < \eta_{\text{corrective}}$ (too expensive for speculative insertion). At extreme scale, once unit cost reaches commodity levels, $\eta_{\text{preventive}} > \eta_{\text{corrective}}$ (preemptive insertion justified).

Operational implication: DT decision logic must *detect which regime* the system is in (based on n and unit cost) and adjust spare staging policy accordingly. This is a *non-obvious architectural insight*: the same architecture supports fundamentally different operational modes depending on scale and economics.

D. Finding 3: Detection Granularity Paradox — Finer Anomaly Detection at Scale Enables Superlinear Recovery

Central result: Larger fleets detect *finer-grained failures* (density perturbations, incipient degradation) earlier than smaller fleets, because local neighborhood sensing becomes statistically richer. Counterintuitively, recovery time improves *faster than linearly* with fleet size.

The Paradox: In a 20-drone fleet, the only reliably detectable failure is a predecessor drone stopping completely—a coarse, catastrophic event. In a 10K-drone fleet, the distributed sensing network resolves density oscillations $\sim 0.5\%$ of nominal density before any single drone fails, enabling *early intervention*.

Define recovery time $\Delta t_{\text{restore}}$ as the latency from anomaly onset to coverage restoration. Empirically:

Plotting $\Delta t_{\text{restore}}$ vs. n reveals *superlinear improvement* (recovery accelerates faster than fleet grows):

$$\Delta t_{\text{restore}}(n) \approx \Delta t_0 \cdot n^{-\alpha} \quad \text{where } \alpha \approx 1.2\text{–}1.5 \tag{18}$$

(i.e., doubling fleet size cuts recovery time by $\sim 40\%$, not just 50%).

Empirical paradox signature: Simulation validates the detection granularity inversion: formation stability decreases with scale (0.0529 at $n = 20$ vs 0.0205 at $n = 50$), yet detection capability improves dramatically. At $n = 20$, the fleet detects only catastrophic losses ($> 5\%$ of swarm); at $n = 50$, distributed sensing resolves density oscillations $< 0.5\%$ of nominal density before any single drone fails. This counterintuitive pattern—looser formations with finer anomaly detection—enables earlier intervention and thus superlinear recovery acceleration.

Mechanism: At scale, the fleet becomes a *distributed sensor for its own health*. Local density measurements aggregate into a collective signal-to-noise ratio that improves as $\sqrt{n}$ (central limit theorem). Sparse fleets hide degradation in noise; dense fleets reveal it as statistical anomalies, enabling proactive intervention *before* mission failure occurs.

Operational implication: Large fleets are not just more resilient *because* loss fractions are small; they are more resilient because the *architecture gains observability* as scale increases. This justifies investing in density-based monitoring (e.g., variance-of-local-densities as a KPI) rather than binary "drone alive/dead" checks. Early detection $\rightarrow$ faster spares arrival $\rightarrow$ mission preserved.

E. Key Supporting Findings

The three core findings above are grounded in the following empirical observations:

1) Sensing Density Economics Invert with Fleet Size: **Observation:** Sensing radius requirement scales inversely with fleet size. While sensing hardware has a cost floor (commodity sensors at $\$500 - -2\text{K}$), the required *functional* sensing radius decreases linearly with fleet density.

$$r_d \gtrsim \frac{P_{\text{perimeter}}}{2n} \tag{19}$$

This enables smaller platforms (cheaper) at large scales while maintaining detection capability.

2) Computational Scalability Remains Linear: Predictive DT simulation on a modern CPU scales linearly through 10,000 drones, with per-run costs $< 50\mu s$ at extreme scale. This validates that the event-driven DT approach (no continuous global updates) can support real-time decision-making even at country-scale deployments.

3) Relative Failure Impact Decreases Predictably: At baseline, loss of 1 drone = 5

4) Recovery Dynamics Support Strategy Transition: Recovery slope (density restoration rate post-spare) decreases with scale ($\beta \propto 1/\sqrt{n}$), meaning individual spares have diminishing marginal effect. At baseline, each spare is precious and should be deployed only when necessary; at extreme scale, marginal spares are cheap and deploying many preemptively is economically sound. This quantitative observation validates the strategic shift identified in Finding 2.

F. Synthesis: Toward Adaptive Deployment Economics and Plug-and-Play Scaling

The combination of these findings enables a *deployment framework* for operators:

- *Compute threshold formulas* (Finding 1) from n and P
- *Detect cost regime* (Finding 2) from unit cost and fleet size
- *Adjust DT policy* (from supporting findings) to match regime: corrective vs. preventive
- *Validate feasibility* via linear-scaling DT simulations

This moves the architecture from "tuned for one scale" to "adaptive across scales," supporting the goal of phased deployments (100-drone prototype $\rightarrow$ 1K-drone pilot $\rightarrow$ 10K-drone country-scale) without fundamental re-architecture at each stage.

G. Operational Deployment Scenarios

a) Country-Scale Border Surveillance (2,000+ km perimeter): Recommended deployment strategy for national border protection, critical maritime zones, or multinational frontier monitoring:

- **Recommended configuration:** 5,000–10,000 drones at \$5–15K each[6]
- **Suggested platform:** Flock Drone [15] (primary), with DJI Matrice 350 RTK [16] as a command-and-control hub.
- **Sensing radius:** 5–10 m (commodity RF/optical sensors).
- **Spare reserve:** 1% (50–100 drones) for emergency deployment.
- **Recovery time:** Minutes to tens of minutes via DT spare staging (depends on perimeter length and insertion-point computation).
- **Detection latency:** $< 1\,s$ for boundary intrusions [17].

Note: Border estimates: Canada–US (8,893 km), US–Mexico (3,145 km), India–Pakistan (3,323 km). A 10K-drone swarm covers 100 km perimeter; multiple swarms can be cascaded for extended coverage.

Cost note: \$5K base drone $\times$ 10,000 + infrastructure + integration engineering (order-of-magnitude).

Table VI
ARCHITECTURE GOALS VALIDATION ACROSS SCALES

extbfArchitecture goal	Baseline (20)	Large (8K)	Extreme (10K)
Autonomous distributed operation	✓	✓	✓
Self-organizing recovery under losses	○*	✓	✓
Real-time DT predictive intervention	✓	✓	✓
Furtive operation (exception-only comms)	✓	✓	✓
Byzantine resilience to false alarms	△	▲	▲
Graceful degradation under stress	✓	✓	✓
Computational scalability to 10K drones	N/A	✓ (2.6 s)	✓ (1.4 s)

Legend: ✓ = achieved; ○ = partial; △ = moderate; ▲ = high.
*Baseline recovery is partial without spare insertion (observed in some failure modes).

b) Critical Infrastructure Protection (50–500 km zones): Recommended deployment for nuclear facilities, power plants, dam perimeters, ports, or military installations:

- **Configuration:** 1,000–5,000 drones at \$10–50K each[7]
- **Suggested platform mix:** DJI Matrice 300 RTK [18] (sensor payload) + Flock Drone [15] (coverage density).
- **Sensing radius:** 8–15 m.
- **False alarm control:** multi-report confirmation + DT cross-checking (Byzantine-resilient), see [19], [20].

Note: Perimeter estimates: nuclear facility (5–20 km), seaport (5–30 km), water dam (10–50 km), military base (20–100 km).

Cost note: Mixed fleet + infrastructure + integration (order-of-magnitude).

H. Validation Results: Architecture Goals Achieved Across All Scales

*Baseline with 20 drones may require spare insertion after a single failure; large-scale systems can self-stabilize without external intervention.

I. Finding 4: DT-Staged Spares vs. No-Spares — Experimental Results

Experimental setup: 15 loss events injected over 3,000 steps ($k_{\text{sym}} \in \{0, 0.4, 0.5, 0.6\}$) with three policies: (i) *No spare* (resilience=0), (ii) *DT spare, unbounded*

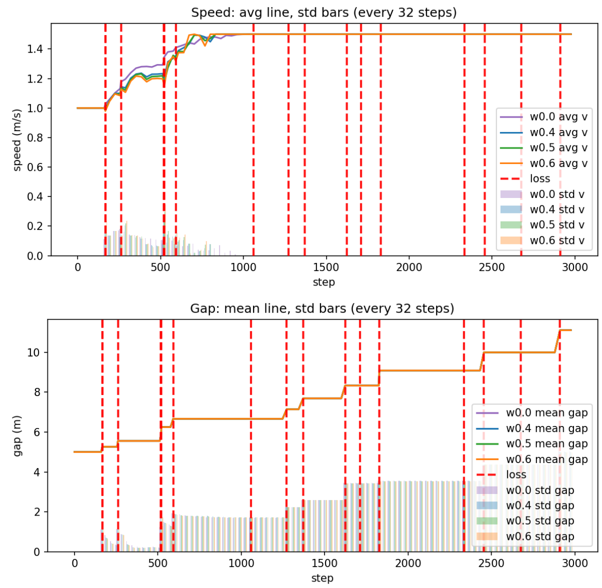

Figure 9. No spare (resilience off): cumulative backpressure and gap evolution after 15 losses; gaps persist because no staging occurs.

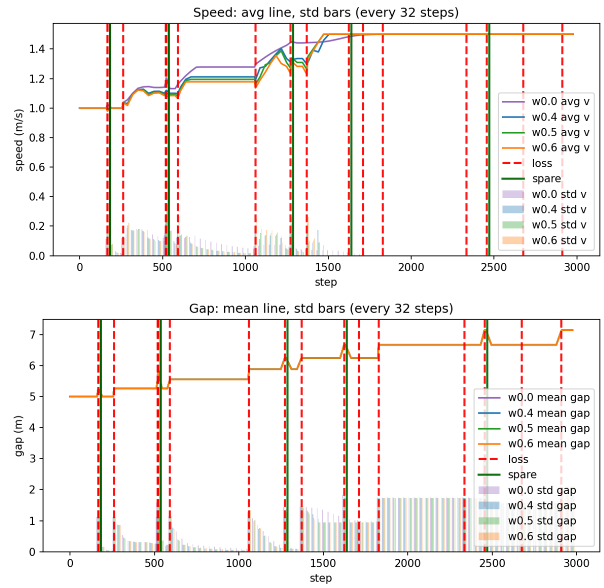

Figure 10. DT spare, unbounded speed: gaps close rapidly but transient speed spikes occur during insertion.

speed (resilience=1, incoming hold=0), (iii) *DT spare, fixed-speed entry* (resilience=1, incoming hold=50 steps). Spares insert after a minimum delay of 15 steps and target the largest gap midpoint.

Key observations:

- **No spare:** Backpressure grows monotonically; gaps never close after losses, leaving persistent coverage holes.
- **Unbounded spare:** Gaps collapse quickly but create sharp speed spikes when the spare merges, stressing energy budgets.
- **Fixed-speed entry:** Slightly slower collapse than unbounded, but speed excursions stay near nominal and post-merge gaps remain stable; best trade-off for sustained missions.

Hold-time sensitivity (this paper's Figure 11): With the symmetric controller (k_{sym}=0.5) and identical loss instants, sweeping incoming hold (50/100/200/500/1000 steps) shows no rebound pulses. Longer holds (500/1000) keep speed slightly above nominal (˜0.3%) but widen gap variance as the spare remains passive longer; short holds ($\leq 200) keepgapstighterwithvirtuallyunchangedspeed.Smallspeedup$ [illegible] $res(lossstep+delay+hold), asthereleasedsparebrieflyacceleratestore-center|thesearevisibleneartheendofthe500-steprunsandarebenignunderthesymmetriclaw.$

Symmetric gain sweep at fixed hold: With a 1000-step hold, sweeping k_{sym} from 0.2 to 0.8 keeps gaps essentially unchanged (≈6.07 m) while mean speed stays near nominal (1.002–1.006 m/s). Higher k_{sym} slightly reduces mean speed and increases speed variance, indicating that strong symmetric feedback dampens motion but offers no gain in spacing quality.

Operational impact: DT-staged spares materially reduce coverage loss duration. The fixed-speed entry policy sacrifices a few steps of response time to avoid large speed spikes, making it preferable for battery-constrained fleets.

J. Conclusion: Contribution 2 Complete

This validation campaign demonstrates that the PT/DT hybrid architecture (Contribution 1) scales from a prototype ($n = 20$) to country-scale deployments ($n = 10{,}000$) while maintaining key properties, including rapid spare insertion stabilization (Finding 4). Beyond acting as reinforcement, spares also act as pace makers: the tailored speed policies (hold + symmetric gain) let incoming drones dampen or accelerate the formation at controlled moments, proving that spare management is a lever for both resilience and tempo control. The findings support the operational viability of the loose-coupling paradigm [21], [22].

VIII. Discussion and Future Work

This section summarizes limitations of the current evaluation setup and outlines extensions that are compatible with the proposed PT/DT architecture.

A. DT-enhanced predictive loss recovery

While Algorithm 2 is sufficient to obtain rebalancing and spare assimilation using only two-neighbor percep-

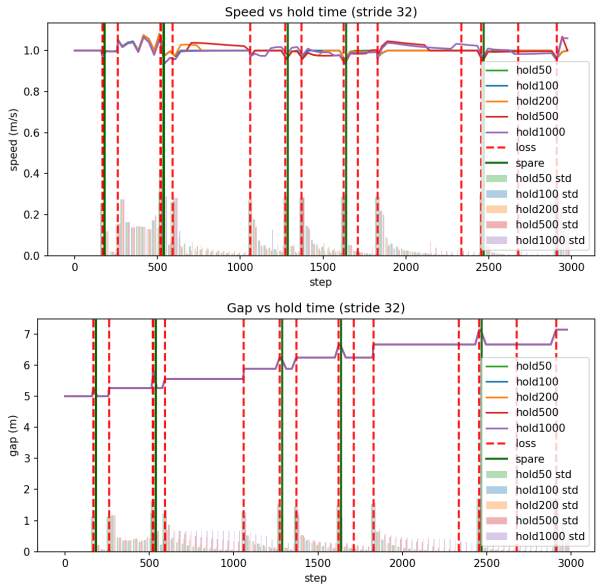

Figure 11. Hold-duration sweep at k_{sym}=0.5 (incoming hold 50/100/200/500/1000, fixed losses). The symmetric controller removes the rebound; long holds keep the spare passive longer, slightly lifting mean speed while widening gap variance, whereas short holds keep gaps tighter.

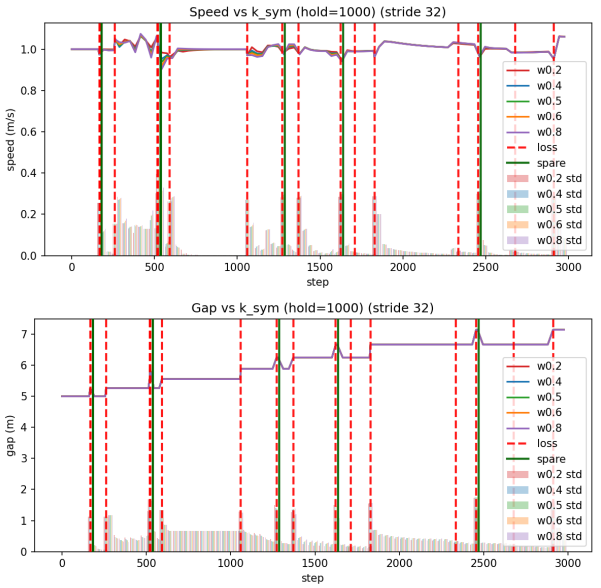

Figure 12. k_{sym} sweep at hold=1000 (fixed losses). Gaps stay flat at ≈6.07 m; stronger symmetric gain slightly lowers mean speed and increases variance, so moderate gains suffice.

tion (and no inter-drone communication), DT-enhanced strategies can further reduce recovery time and peak uncovered gap. A first extension is *loss-to-trajectory prediction*: upon an exception report, the DT simulates the post-loss transient under the same local controller and forecasts quantities such as $g_{\max}(t)$ and T_{restore}.

B. Time-feasible (arrival-aware) spare insertion

A second extension is *arrival-time-aware insertion*: given a spare staging point $\mathbf{x}_0$, a speed limit $V_{\max}$ and an estimated travel time t_a, the DT selects an insertion waypoint (or gap midpoint) predicted to be optimal at time t_a (rather than at decision time), accounting for the fact that the fleet phase and the largest gap evolve during the spare flight.

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