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Development of UAV Swarm Ad-Hoc Network Communication Technology for Emergency Scenarios: A Review

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***Abstract*—Major disasters such as earthquakes, floods, and wildfires can rapidly destroy terrestrial communication infrastructure, producing an extreme operating environment in which power, road, and network outages compound one another. Owing to their rapid deployability, flexible networking, and three-dimensional mobility, unmanned aerial vehicle (UAV) swarms are being studied as a flexible component of emergency communication systems. This paper reviews UAV swarm ad-hoc network communication technology for emergency scenarios. It examines the technical characteristics and applicability boundaries of three network architectures—flat, hierarchical clustering, and space-air-ground integrated—and surveys recent advances in routing and medium access, intelligent networking optimization, and transmission and security assurance. Particular attention is given to the reported performance and applicability of emerging approaches, including reinforcement-learning-based adaptive routing, decentralized federated learning, digital twins, and semantic communication, under highly dynamic and resource-constrained conditions. Drawing on studies of emergency routing, post-disaster data collection, semantic forwarding, and multi-layer coverage, the paper assesses current validation methods and outlines research directions in energy use, scalability, security, resilience, and standardization. Its contribution is a cross-layer comparison that relates architecture choices to protocol requirements, implementation costs, and validation maturity.**

***Index Terms*—UAV swarm; Ad-hoc network; Emergency communication; Routing protocol; Federated learning; Semantic communication; Space-air-ground integration**

I. Introduction

Major natural disasters can damage terrestrial communication infrastructure within a short period, creating conditions in which base-station outages, fiber cuts, and power failures occur together. Reliable information channels support situational awareness, command, dispatch, and search operations during time-sensitive response. Portable satellite terminals and emergency communication vehicles provide established communication functions, while UAVs add mobile relaying, data collection, and edge-computing options [1]. Aerial self-organizing networks built on UAV swarms are therefore an active research direction for emergency communication [2].

A UAV swarm ad-hoc network, commonly referred to as a flying ad-hoc network (FANET), extends the mobile ad-hoc networking paradigm to three-dimensional, highly dynamic settings. Compared with terrestrial mobile ad-hoc networks and vehicular ad-hoc networks, FANETs often operate with higher node mobility, faster topology changes, lower node density, and stronger sensitivity to altitude, attitude, and blockage [7]. Emergency scenarios add abrupt mission onset, limited energy replenishment, complex electromagnetic conditions, and possible loss of ground infrastructure. These conditions motivate protocols and architectures designed for dynamic aerial platforms. The present review therefore focuses on network architecture, routing and access, intelligent optimization, and secure transmission.

Studies of NTN evolution describe closer integration between terrestrial and satellite networks from 5G toward prospective 6G systems [2], [3]. Expanding low-Earth-orbit (LEO) constellations provide a backhaul option for UAV swarms equipped with compatible terminals. Reviews of 3GPP activities for UAV connectivity identify cellular and NTN mechanisms that can connect aerial networks with broader communication infrastructure [5]. In parallel, machine learning methods are being studied for routing decisions, resource allocation, and mission coordination in dynamic networks [6]. Research on service-oriented architectures for space-air-ground integrated networks (SAGINs) also provides a framework for cross-domain resource coordination [4]. Within this context, this paper reviews the architectural forms, key technologies, application validation, and open challenges of UAV swarm ad-hoc networking for emergency scenarios. The analysis connects architecture choice with protocol requirements, implementation trade-offs, and validation maturity.

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II. Network Architectures for Emergency Swarm Ad-Hoc Networking

In a flat architecture, all UAV nodes are peers that form a mesh topology directly over multi-hop wireless links, without any centralized control entity. Such networks avoid a centralized point of failure and can reconstruct neighbor relationships after node loss, making the architecture suitable for small-scale, rapid-response missions. As the node count grows, flooding-based control traffic increases and routing performance can deteriorate, so scalability remains a design constraint [7]. Position-assisted forwarding can reduce control traffic, although sparse deployment and communication voids still challenge delivery. Flat architectures are therefore suitable for spatially limited tasks or for intra-cluster networking within a hierarchical architecture.

A hierarchical clustering architecture partitions the swarm into clusters in which cluster heads handle intra-cluster aggregation and inter-cluster forwarding, yielding a two- or multi-tier topology. This organization can reduce routing-table size and control traffic, while load balancing distributes forwarding work across cluster heads [9]. Dynamic clustering and head-rotation strategies address concentrated energy consumption and cluster-head failure, and simulation studies evaluate election schemes based on connectivity, residual energy, and relative mobility [8]. Bio-inspired optimization has also been introduced into inter-cluster routing, where hybrid ant-colony protocols maintain alternative paths through pheromone-based updates [16]. Hierarchical architectures therefore provide a practical option for multi-UAV monitoring and tiered data aggregation.

A space-air-ground integrated architecture places high-altitude platforms and LEO satellites above the UAV swarm and connects downward to terrestrial networks and portable terminals, forming a multi-layer communication system. LEO satellite links can extend backhaul beyond terrestrial coverage, while the UAV layer handles access and data aggregation [2], [4]. Coverage-modeling studies indicate that cross-layer paths can raise connectivity probability under the evaluated conditions [10]. Integrating terrestrial and non-terrestrial networks also introduces interference-coordination and mobility-management problems that connect spectrum, beam, and handover design [11]. Satellite backhaul is therefore a conditional option for missions that require coverage beyond available terrestrial or aerial relays. Its use adds compatible terminals, antenna and link-budget requirements, energy consumption, handover control, and propagation delay.

Architectural evaluation requires a model of three-dimensional mobility and topology dynamics. Mobility models shape the estimated distribution of link lifetimes and topology changes used to evaluate routing protocols [7]. Correlated-mobility models can represent formation flight, area scanning, and target orbiting more directly than purely random motion. Multistate network analysis represents node failure, link degradation, and information-exchange capacity within one resilience model [12]. Table I compares the three architectures with respect to scalability, latency, robustness, and typical use.

III. Key Communication Technologies

Beneath the architectural level, the capability of an emergency swarm ad-hoc network is determined by a set of tightly coupled key technologies. This paper groups them into four domains—network architecture, routing and medium access, intelligent networking optimization, and transmission and security assurance—and maps them onto typical emergency applications, yielding the classification framework shown in Fig. 1. The framework emphasizes how these domains act in concert on a shared underlying problem: operation under high dynamics, tight constraints, and mission-driven traffic; it also provides the organizing thread for the discussion that follows. The elements in the figure are not independent of one another: routing decisions rely on channel-awareness results, while intelligent optimization in turn supplies parameters to routing and access. Each domain is examined in turn below.

Reliable networking presupposes accurate modeling of air-to-air and air-to-ground channels. Equations (1)–(3) give a link-level model for one scheduling interval. Let $\mathcal{N}$ denote the UAV-node set. UAV $i \in \mathcal{N}$ is the transmitter, UAV $j \in \mathcal{N}$ is the intended receiver, and d_{ij} is their three-dimensional separation in meters. In (1), $\mathrm{PL}(d_{ij})$ is mean path loss in decibels, f_c is carrier frequency in hertz, c is the speed of light in meters per second, and η_{LoS} and η_{NLoS} are environment-specific excess losses in decibels. In (2), $P_{\mathrm{LoS}}(\theta_{ij}) \in [0,1]$ is the LoS probability, θ_{ij} is the elevation angle, a is an environment-dependent sigmoid offset, and b is its slope parameter; θ_{ij} and a use the same angular unit and b uses its reciprocal. In (3), R_{ij} is the instantaneous achievable rate in bits per second, B is channel bandwidth in hertz, P_t is the power of transmitter i, and σ^2 is receiver noise power. The large-scale power gain G_{ij} incorporates path loss and antenna gains, while h_{ij} is the small-scale fading coefficient of the desired link. The interference set $\Phi_I \subseteq \mathcal{N} \setminus \{i,j\}$ contains concurrently transmitting UAVs; for each $k \in \Phi_I$, P_k, G_{kj}, and h_{kj} denote its transmit power and channel terms toward receiver j. All power terms in (3) use the same linear unit, and aggregate co-channel interference is treated as noise. These definitions support consistent use of the model in routing metrics, power control, and topology optimization.

$$\begin{aligned}\mathrm{PL}(d_{ij}) = 20\lg\left(\frac{4\pi f_c d_{ij}}{c}\right) + \eta_{\mathrm{LoS}} P_{\mathrm{LoS}}(\theta_{ij}) \\ + \eta_{\mathrm{NLoS}}\left[1 - P_{\mathrm{LoS}}(\theta_{ij})\right]\end{aligned} \tag{1}$$

$$P_{\mathrm{LoS}}(\theta_{ij}) = \frac{1}{1 + a\exp[-b\,(\theta_{ij} - a)]} \tag{2}$$

$$R_{ij} = B\log_2\left(1 + \frac{P_t G_{ij}\,|h_{ij}|^2}{\sum_{k\in\Phi_I} P_k G_{kj}\,|h_{kj}|^2 + \sigma^2}\right) \tag{3}$$

Routing is a major research area in swarm ad-hoc networking, with current work spanning rule-based and learning-based designs. Conventional topology- and position-based protocols rely on periodic neighbor discovery and greedy geographic

TABLE I
COMPARISON OF UAV SWARM AD-HOC NETWORK ARCHITECTURES FOR EMERGENCY SCENARIOS

Architecture	Scalability	End-to-End Latency	Robustness	Typical Emergency Use
Flat ad-hoc	Low to medium	Low within a few hops; degrades with scale	No single point of failure; flooding overhead grows rapidly	Village-level rescue, local hotspot coverage
Hierarchical clustering	Medium to high	Medium (intra-/inter-cluster relaying)	Sensitive to cluster-head failure; mitigated by rotation and load balancing	Wide-area monitoring with tiered data aggregation
SAGIN-assisted (optional LEO backhaul)	High	Medium to high (satellite backhaul delay)	Additional path diversity when compatible links are available	Trans-regional relief when terrestrial and aerial backhaul are insufficient

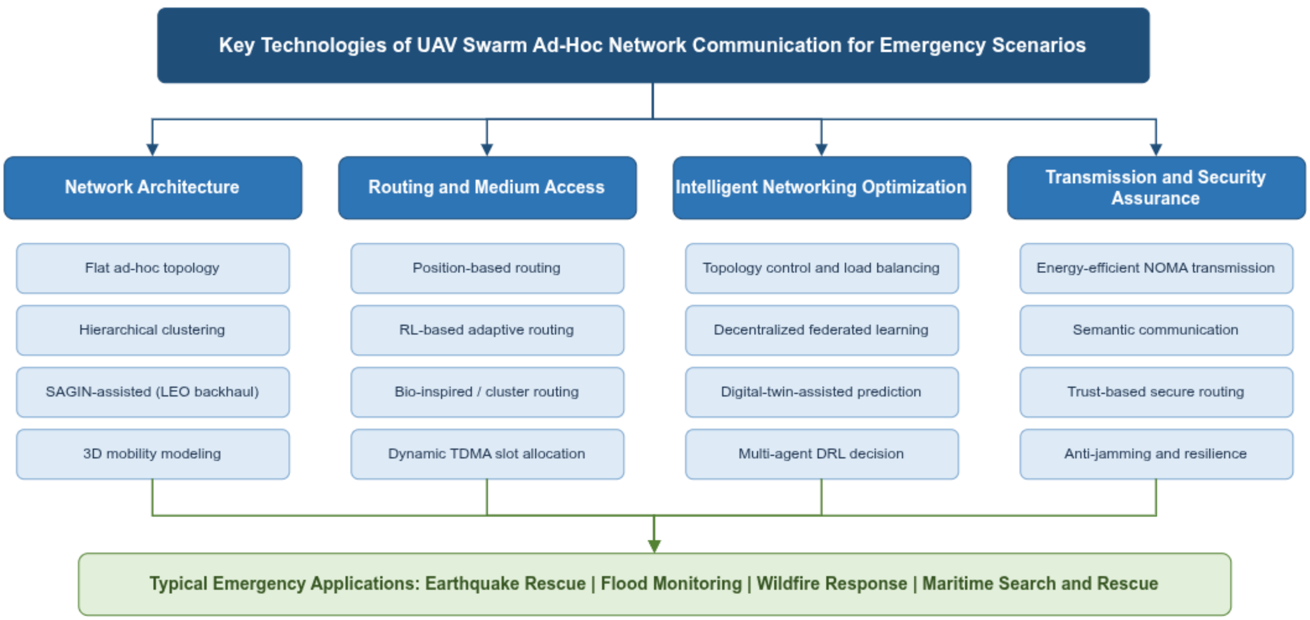

Fig. 1. Classification framework of key technologies for UAV swarm ad-hoc network communication in emergency scenarios

forwarding; path maintenance becomes more difficult under high-speed maneuvering and sparse deployment [7]. Cluster-based routing addresses scalability through hierarchical organization, and dynamic load balancing distributes traffic across cluster heads [8], [9]. Reinforcement-learning (RL) routing formulates next-hop selection as a sequential decision problem in which each node updates its forwarding policy according to a utility function combining delay, energy, and link stability [14]. Q-learning-aided routing has been evaluated through large-scale cognitive-UAV-swarm simulations for emergency communication, indicating the potential of utility-driven forwarding in dynamic settings [15]. Metric designs that combine energy consumption and mobility provide another basis for route selection [17], and surveys of machine-learning routing organize the method categories and open problems [13]. Table II summarizes and compares representative routing schemes.

Medium access control shapes channel utilization and scheduling delay in dense swarms. As node counts grow, contention-based access can encounter more collisions, motivating research on deterministic time-division methods. Distributed slot allocation decomposes global scheduling into local negotiation, and coalition-formation protocols seek low-conflict assignments without a central coordinator [18]. Clustered networks can also combine time division within clusters with frequency separation between clusters. At the spectrum level, cognitive access allows opportunistic use of idle bands [15]. Cross-layer design of access and routing remains an active direction for improving end-to-end scheduling.

The open wireless environment of an emergency network exposes it to node capture, route falsification, and malicious jamming, so security assurance must be designed jointly with the networking protocols themselves. Trust management converts each node's behavioral history into a routing metric, and fuzzy trust models evaluate the trade-off between malicious-node detection and false alarms [19]. Against jamming, frequency hopping, power control, and relay reconfiguration can be combined with learning methods to support transmission under adversarial conditions. Multistate network models jointly represent topology redundancy, node states,

TABLE II
REPRESENTATIVE ROUTING SCHEMES FOR UAV SWARM AD-HOC NETWORKS

Category	**Core Mechanism**	**Strength**	**Limitation**
Topology-/position-based [7]	Mobility-aware geographic forwarding	Low overhead, simple implementation	Delivery degrades in voids and sparse areas
Cluster-based [8], [9]	Dynamic clustering with load balancing	Scalable and energy-aware	Cluster-maintenance overhead
RL-/Q-learning-based [14], [15]	Online utility-driven next-hop learning	Adapts to topology dynamics; emergency-oriented utility	On-board training and convergence cost
Bio-inspired hybrid [16]	Ant-colony inter-cluster path optimization	Path diversity and fault recovery	Parameter sensitivity
Joint energy–mobility metric [17]	Energy- and mobility-aware route metric	Prolongs network lifetime	Requires accurate state information

and information-exchange capacity, enabling quantitative resilience assessment under faults and attacks [12]. Physical-layer security and lightweight authentication, matched to the computational limits of UAV platforms, complement these network-layer mechanisms. Mission priority can guide the balance between security overhead and networking performance.

Semantic communication provides a task-oriented approach for bandwidth-constrained disaster links. In contrast to bit-exact transmission, it extracts and conveys task-relevant information to reduce transmitted data volume [20]. Studies of aerial semantic communication evaluate semantic compression and resource allocation for post-disaster image backhaul and situation reporting [21]. Multi-UAV cooperative semantic forwarding jointly considers semantic extraction and network forwarding in simulated post-disaster data-collection tasks [22]. Current research therefore identifies semantic communication as one option for coordinating application-level information and ad-hoc network resources.

IV. NETWORKING OPTIMIZATION AND INTELLIGENT DECISION-MAKING

The joint configuration of positions, power, and network resources can be represented by the generic single-interval problem in (4). The node set is $\mathcal{N}$, and $\mathbf{q}_i \in \mathcal{Q}_i$ and $\mathbf{p}_i \in \mathcal{P}_i$ denote the feasible position and power vectors of UAV i. The vector $\mathbf{x} \in \mathcal{X}$ contains feasible channel, slot, and association decisions. For each of the K active traffic flows, $R_k(\mathbf{q}, \mathbf{p}, \mathbf{x})$ is its achieved rate and $U(\cdot)$ is a selected network-utility function. The energy used by UAV i during the interval is $E_i(\mathbf{q}, \mathbf{p}, \mathbf{x})$, with budget $E_i^{\max}$. The matrix $\mathbf{L}(\mathbf{q})$ is the Laplacian of the undirected communication graph induced by the node positions, and $\lambda_2(\mathbf{L}) > 0$ requires that graph to remain connected. Particular studies specify the feasible sets, utility, channel model, and interval length according to their mission assumptions.

$$\begin{aligned}
\max_{\mathbf{q},\mathbf{p},\mathbf{x}} \quad & \sum_{k=1}^{K} U(R_k(\mathbf{q},\mathbf{p},\mathbf{x})) \\
\text{s.t.} \quad & E_i(\mathbf{q},\mathbf{p},\mathbf{x}) \le E_i^{\max}, \quad \forall i \in \mathcal{N}, \\
& \mathbf{q}_i \in \mathcal{Q}_i, \quad \mathbf{p}_i \in \mathcal{P}_i, \quad \forall i \in \mathcal{N}, \\
& \mathbf{x} \in \mathcal{X}, \quad \lambda_2(\mathbf{L}(\mathbf{q})) > 0
\end{aligned} \tag{4}$$

The formulation exposes the principal costs of joint optimization. Mobility changes propulsion energy, transmit power changes both rate and interference, and more detailed resource decisions increase signaling and computation. Studies use convex relaxation, alternating optimization, heuristic search, and learning-based methods according to the variable structure and available on-board resources [17], [29]. Method selection therefore depends on which communication, computation, and energy costs the mission can accommodate.

Federated learning (FL) provides a framework for distributed model training without exchanging raw local data. Decentralized FL removes dependence on a terrestrial parameter server by allowing nodes to exchange model updates with their neighbors, which matches the serverless organization of ad-hoc networks [23]. Numerical simulations of fully decentralized FL evaluate cooperative model updating in UAV-swarm settings [24]. Studies spanning computing, sensing, and semantics also describe the resource constraints of distributed learning in UAV swarms [25]. Over-the-air aggregation uses wireless signal superposition to combine model updates and can reduce communication overhead under the evaluated system model [26]. Model heterogeneity, non-independent and identically distributed data, and changing node participation remain central design issues.

Digital twins support network rehearsal and prediction by maintaining a virtual representation of system state. Cooperative digital-twin frameworks study multi-UAV state synchronization, model updating, and coordinated sensing within a shared decision loop [27]. Combining digital twins with FL distributes model construction and update tasks across network nodes [26]. Predictive communication incorporates short-horizon channel or traffic forecasts into protocol decisions, allowing resources to be configured before expected state changes [28]. Lightweight modeling and incremental synchronization are therefore important for matching twin updates to on-board computing and backhaul resources.

Multi-agent reinforcement learning (MARL) provides a framework for swarm-level cooperative decision-making. The centralized-training, decentralized-execution paradigm allows policies to be trained with shared information while individual nodes execute local policy networks [6]. For joint decisions

TABLE III
TYPICAL EMERGENCY APPLICATIONS AND VALIDATION STATUS OF UAV SWARM AD-HOC NETWORKING

Scenario	Networking Approach	Scale / Platform	Validation Level
Emergency routing [15]	Cognitive UAV swarm with Q-learning routing	650–1000 simulated UAVs	Numerical simulation
Post-disaster IoT data collection [29]	UAV base station with NOMA transmission	Single UAV serving multiple gateway clusters	Simulation and analysis
Post-disaster relief information delivery [21], [22]	Multi-UAV semantic extraction and forwarding	Low-altitude multi-UAV group	Simulation
Wide-area monitoring and backhaul [4], [10]	Multi-layer terrestrial, aerial, and satellite network	System-level multi-layer network	Architectural analysis and coverage modeling
FANET clustering [9]	Hierarchical clustering with load balancing	Simulated multi-UAV network	Simulation

spanning routing, slots, power, and trajectories, multi-agent models can represent cooperation and competition among network nodes [25]. Reward functions can incorporate mission priority and energy cost, while digital-twin environments can support policy evaluation across changing network conditions [27]. Interpretability and policy verification remain relevant to deployment in safety-constrained missions.

V. Typical Emergency Applications and Experimental Validation

Application-oriented studies connect networking methods with emergency communication requirements. Large-scale simulations of cognitive UAV swarms evaluate utility-driven routing for emergency traffic [15]. Post-disaster Internet-of-Things (IoT) studies combine NOMA transmission with a UAV base station to collect data from multiple gateway clusters under energy constraints [29]. Dynamic-clustering simulations evaluate load balancing and cluster-head selection in FANETs, providing mechanisms relevant to multi-UAV monitoring and data aggregation [9]. These studies address uneven traffic demand through routing, access, and resource-allocation methods.

Post-disaster semantic-communication studies evaluate multi-UAV data collection, semantic extraction, and forwarding through simulation [21], [22]. For offshore and other wide-area settings, coverage models of integrated space-air-ground-sea networks examine how terrestrial, aerial, and satellite layers contribute to connectivity [10]. Service-oriented SAGIN architectures complement this physical-layer view by defining mechanisms for coordinating heterogeneous resources [4]. Together, these studies provide design options for emergency information collection and wide-area backhaul.

Simulation and analytical modeling are the main validation methods in the studies summarized here. Table III reports the networking approach, modeled platform scale, and validation type for each selected study. Shared emergency-networking scenarios, metrics, and baseline protocols would improve comparison across methods and support subsequent field evaluation.

A. Cross-Layer Synthesis and Design Trade-offs

Across the reviewed studies, architecture choice sets the main operating trade-off. Flat networking limits coordination infrastructure but incurs increasing discovery, flooding, and contention costs as the swarm grows. Hierarchical clustering contains control traffic and supports aggregation, while cluster formation, head rotation, and inter-cluster forwarding consume energy and signaling resources. Satellite-assisted SAGIN extends the available backhaul when terrestrial and aerial relays do not meet the coverage requirement, but requires compatible radio equipment and adds link management, energy use, and delay. Intelligent methods introduce a second trade-off: RL and MARL exchange fixed protocol rules for training and convergence costs, FL avoids raw-data exchange but requires repeated model synchronization, semantic communication reduces payload volume at the cost of task-specific models, and digital twins require state collection and model updates. The current evidence base is dominated by simulation and analytical modeling, so these trade-offs are more consistently characterized than field performance. This cross-layer comparison identifies the mission range, swarm scale, available backhaul, energy budget, and validation level as the main factors for selecting a design.

VI. Challenges and Outlook

Energy limits constrain communication, computation, and mobility in UAV swarm networks. Energy-aware routing studies address this trade-off by combining node energy state with mobility information [17]. Scalability remains a parallel challenge because additional nodes increase control traffic, interference, and scheduling complexity [13]. Security and survivability research combines resilience metrics, trust management, and anti-jamming transmission [12], [19]. Shared scenarios, metric definitions, and baseline protocols would make evaluations easier to compare.

Research toward 6G NTN continues to examine closer integration of satellite and terrestrial networks [2], [3]. For UAV swarms, satellite backhaul is one supplementary or backup option when terrestrial and aerial relays do not provide the required reach or continuity [5]. Its suitability depends on terminal capability, energy budget, link availability, handover control, and tolerable delay. Cooperative sensing and communication methods developed for low-altitude networks could also be adapted to search-and-rescue localization tasks [30]. Predictive communication, digital twins, and semantic communication provide complementary approaches to forecasting network state, evaluating decisions, and reducing transmitted data [20], [27], [28]. Future evaluation can compare these methods under common mission, energy, traffic, and failure assumptions.

VII. Conclusion

This paper has reviewed UAV swarm ad-hoc network communication technology for emergency scenarios. Flat architectures favor local deployment, hierarchical architectures organize larger swarms through tiered forwarding, and space-air-ground integration adds wide-area backhaul when its additional equipment, energy, and delay costs are acceptable. Routing, access, learning, semantic communication, digital twins, and security mechanisms address different parts of the same design problem, but each exchanges communication overhead for computation, coordination, model maintenance, or specialized hardware. Application-oriented evidence is concentrated in simulation, analytical modeling, and small-scale prototypes for emergency routing, post-disaster data collection, semantic forwarding, and multi-layer coverage. The resulting synthesis provides a basis for matching architecture and protocol choices to mission range, swarm scale, backhaul availability, energy budget, and validation maturity. Terrestrial and aerial links form the local communication basis, while satellite links provide an optional extension for missions that require wider reach.

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