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FANET DATASET: UAV COMMUNICATION SCENARIOS IN NS-3.40

Ali Moussaoui[1] and Hicham Lakhlef[2]

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ABSTRACT

Flying Ad hoc Networks (FANETs) enable communication among unmanned aerial vehicles (UAVs) in highly dynamic and infrastructure-less environments. However, high mobility; limited onboard energy and rapidly changing network topology make reliable communication and Quality of Service (QoS) assurance particularly challenging. This paper presents a publicly available FANET dataset generated through detailed simulations using NS-3.40. The dataset consists of eight communication scenarios that systematically vary node density, mobility speed, transmission range, energy levels, traffic type and communication architecture. For each scenario, the dataset provides packet-level traces, UAV mobility and energy states, QoS metrics and routing information derived from the OLSR protocol. The dataset is designed to support performance analysis, protocol benchmarking and the development of energy-aware and AI-driven routing strategies for FANETs. By releasing this dataset on Zenodo, we aim to facilitate reproducible experimentation and provide a practical reference for future research on UAV communication networks.

KEYWORDS

FANET, UAV, Dataset, QoS, NS-3, OLSR, Ad hoc networks.

1. INTRODUCTION

Flying *Ad hoc* Networks (FANETs) consist of unmanned aerial vehicles (UAVs) that communicate in a distributed and infrastructure-less manner. Their ability to rapidly deploy, self-organize and operate in three-dimensional space makes them attractive for applications, such as disaster response, environmental monitoring, precision agriculture, search and rescue, aerial mapping and surveillance [1]-[2]. These applications typically operate under strict time, energy and reliability constraints.

FANETs exhibit characteristics that clearly distinguish them from other *ad hoc* network paradigms. UAVs move at relatively high speeds, operate in three-dimensional space and experience frequent link disruptions due to dynamic topology changes. At the same time, UAVs must satisfy demanding Quality of Service (QoS) requirements, including low latency, sufficient throughput and reliable packet delivery, while relying on limited onboard energy resources [3]. These constraints significantly complicate network design and protocol optimization.

From a conceptual standpoint, FANETs can be viewed as a specialized sub-class of Mobile *Ad hoc* Networks (MANETs), alongside Vehicular *Ad hoc* Networks (VANETs) and Wireless Sensor Networks (WSNs). All these paradigms share the principle of decentralized, infrastructure-free communication. However, FANETs operate in an aerial environment characterized by unrestricted three-dimensional mobility and rapidly evolving network topologies, which fundamentally differentiates them from terrestrial networks [4]-[5]. As a result, routing and QoS assurance are considerably more challenging in FANETs than in ground-based *ad hoc* networks [6].

Reliable routing remains one of the central challenges in FANET research. High mobility and frequent link breaks make it difficult to maintain stable end-to-end paths [7]-[8]. Classical routing protocols, such as OLSR [9] and AODV [10], originally designed for relatively stable MANET environments, often struggle to meet FANET-specific QoS requirements. These traditional protocols, based only on shortest paths, are no longer well suited to FANETs. Newer adaptive protocols (e.g., A-Geo [23]) illustrate the trend toward intelligent routing. Beyond such deterministic schemes, machine learning has also been explored for FANETs. Machine-learning approaches fall into three categories: supervised, unsupervised and reinforcement learning. The first two require static datasets, which are still scarce; the third learns interactively, but can benefit from validation benchmarks. The development of such intelligent routing

1. A. Moussaoui is with Department of Computer Science, Intelligent Systems and Cognitive Computing (ISCC) Laboratory, University Mohamed El Bachir El Ibrahimi, Bordj Bou Arréridj, Algeria. Email: ali.moussaoui@univbba.dz
2. H. Lakhlef is with Univ. Bordeaux, CNRS, Bordeaux INP, LaBRI, UMR 5800, F-33400 Talence, France.

critically depends on realistic and comprehensive datasets [11]-[12]. However, as we detail in the following section, existing datasets either lack the multi-layer information necessary for holistic FANET analysis or rely on ground-mobility assumptions that do not translate to aerial environments.

Despite increasing research activity on UAV communications, publicly available datasets specifically dedicated to FANETs remain scarce. Existing datasets are often narrowly focused on security or intrusion detection and typically lack multi-layer information, such as routing states, mobility traces, energy evolution and QoS dynamics [13]-[14]. Other large-scale *ad hoc* or vehicular datasets rely on two-dimensional ground mobility and simplified assumptions, which limits their applicability to aerial networks [15]-[16]. Consequently, there is a clear need for a general-purpose FANET dataset that provides a holistic view of UAV communication behavior.

To address these specific gaps, the dataset introduced in this paper is designed to systematically capture the three main FANET challenges identified above, high mobility, limited energy and dynamic topology, across eight controlled scenarios. Mobility speeds range from 10 to 20 m/s, initial energy budgets from 100 to 300 J and transmission ranges from 250 to 400 m . For each scenario, the dataset provides not only QoS metrics, but also the underlying packet-level traces, routing states (OLSR) and energy evolution, enabling researchers to isolate or combine these challenging factors in reproducible experiments.

Our dataset is publicly available and can be downloaded from Zenodo using the DOI: https://doi.org/10.5281/zenodo. 19373220 [17]. It is designed to support performance evaluation, protocol benchmarking and AI-driven routing research under varying mobility, energy and communication conditions. By making this dataset publicly available, we aim to facilitate reproducible research and provide a common reference for future studies on FANETs.

The remainder of this paper is organized as follows. Section 2 reviews related work on existing FANET and mobility datasets. Section 3 presents the motivation and scientific relevance of the dataset. Section 4 describes the dataset structure and content. Section 5 details the simulation methodology. Section 6 discusses validation and consistency checks. Section 7 outlines potential applications and Section 8 provides usage guidelines. Finally, Section 9 concludes the paper and discusses future directions.

2. RELATED WORK

In recent years, research on FANETs has received a lot of attention, especially with regard to routing optimization, performance evaluation and the application of AI for adaptive communication [11]-[12]. Numerous studies have made an effort to create or model datasets for the purpose of analyzing FANET behavior; however, the majority of these datasets are still restricted in terms of their breadth, reproducibility and variety of network scenarios.

Compared to datasets created for VANETs and ground-based *Ad Hoc* networks, publicly accessible datasets for Flying *Ad Hoc* Networks (FANETs) are still incredibly rare. Given the unique features of FANETs-high node mobility, quickly changing topology, 3D movement and aerial propagation conditions - that render current datasets inappropriate for aerial contexts, this scarcity is noteworthy. FANGHETS24 is one of the few datasets specifically created for FANETs [13]. It focuses on using early time-series classification of packet interactions to detect gray hole attacks. The dataset is useful for security research, but it can't be used for general FANET networking studies, because it only includes one type of attack and doesn't offer more comprehensive network information, like routing dynamics, link stability, MAC/PHY traces or QoS performance.

UAVIDS-2025 is another pertinent dataset that provides labeled flow records for intrusion detection in UAV swarms and covers a variety of attack types, including wormhole, flooding, Sybil and black hole [14]. The dataset, which was created using NS-3 and realistic mobility, is helpful for assessing IDS models, but is still solely focused on security. Energy consumption, routing evolution, multi-protocol comparisons and low-layer communication logs are not included. Similar to FAN-GHETS24, it concentrates on a particular issue (intrusion detection) rather than offering a flexible dataset for QoS prediction, AI-based routing or FANET performance analysis.

A number of datasets on generic *Ad Hoc* networks are available outside of FANETs, such as Packet Time Delivery on *Ad Hoc* Networks by Rocha and Gradvohl [15]. Ninety thousand simulations covering packet delivery times in different node densities, regions and gateway configurations are included in this dataset. Despite having a wide simulation coverage, it is still predicated on fixed terrestrial *Ad Hoc* assumptions and 2D mobility, lacking the mobility dynamics, aerial channel characteristics and real-time topology variations present in FANETs. Its metrics do not capture multi-layer behaviors pertinent to UAV networks and instead concentrate on delivery delays and failures.

A larger body of datasets originates from VANETs, which, although technologically distinct, illustrate how large-scale open datasets have successfully shaped research in mobile *Ad Hoc* networking. The CN+ dataset, based on real-world vehicle mobility at a signalized intersection, provides a large amount of empirical data for traffic-aware communication studies [18]. However, its constraints-ground mobility, 2D movements and traffic-light-regulated behavior-make it unsuitable for aerial networks. Similarly, the VANET Mobility Dataset integrates real highway mobility traces generated with SUMO and validated against real traffic databases (PeMS) [19]. While influential for mobility and topology studies, its channel model and movement patterns do not translate to 3D free-space UAV mobility.

Another widely used contribution is the Cologne vehicular mobility dataset, which offers 24 hours of synthetic, yet highly realistic, car mobility traces over a 400 km^2 urban area [16]. By modeling both macroscopic traffic flows and microscopic driving behavior, it has significantly improved the realism of VANET simulations. Nevertheless, despite its scale and level of detail, this dataset is limited to terrestrial mobility. It does not include communication traces, aerial dynamics, energy constraints or multi-hop routing information, which restricts its applicability to FANET-related studies. Similarly, the VeReMi dataset has become a well-established benchmark for misbehavior detection in VANETs, providing labeled benign and malicious messages in urban driving scenarios [20]. Although methodologically robust-particularly in its definition of ground truth and attack models-it remains focused on vehicle-to-vehicle safety communications and does not address aerial networking or routing-layer behavior.

Table 1 summarizes the limitations of existing datasets compared to the proposed FANET dataset.

Table 1. Comparison of existing datasets and their limitations.

Dataset	Scope & Coverage	Data Granularity	Limitations	Reproducibility & Accessibility	Key Use Cases
FANGHETS24 [13]	one scenario, grey hole attack	Packet interactions only	Security only, no QoS/routing/ energy	Available	Grey hole detection
UAVIDS2025 [14]	Multiple attacks	Flow records (IDS)	Security only, no low layer traces	NS-3 based	Intrusion detection
Packet Time Delivery [15]	90k simulations, 2D	Packet delivery times	2D, terrestrial, no aerial channel	Available	Delay analysis
Cologne [16]	24 h mobility, 2D	Mobility only	No comm./energy/ routing traces	Public	Vehicular mobility
VeReMi [20]	Urban driving	V2V messages	V2V only, no aerial multihop	Public	Misbehavior detection

Taken together, these datasets reveal two important observations. First, publicly available FANET datasets remain extremely scarce and are often narrowly tailored to specific security use cases, such as intrusion or attack detection. None of the existing datasets provides a holistic, multi-layer view of FANET behavior that jointly captures three-dimensional mobility, routing protocol states, physical-layer effects, link quality variations, QoS metrics and energy dynamics. Second, while VANET datasets clearly demonstrate the scientific value of well-designed mobility and communication traces, their underlying assumptions-ground-constrained motion, stable connectivity patterns and vehicular traffic models -are fundamentally different from those of aerial networks. As a result, they cannot be directly reused for realistic FANET modeling or AI-driven networking research.

These limitations, summarized in Table 1, highlight the need for a general-purpose, AI-ready FANET dataset that reflects the unique characteristics of aerial networks, including realistic UAV mobility, multihop routing dynamics, PHY/MAC interactions and detailed performance metrics. Such a dataset would not only support traditional networking studies, but would also enable machine learning-based applications, such as QoS prediction, routing optimization, anomaly detection, topology evolution forecasting and autonomous swarm coordination. In contrast to existing datasets, the dataset proposed in this work is designed to address this gap by providing a comprehensive, structured and reproducible resource specifically tailored to FANET research.

3. Motivation for Dataset Creation and Research Significance

The increasing complexity of FANETs calls for reproducible and well-documented datasets that enable systematic evaluation of communication protocols and intelligent networking strategies. In practice, the lack of shared data sources makes it difficult to compare results across studies or to assess the robustness of proposed solutions under diverse operating conditions, leading many contributions to rely on custom simulation setups that are hard to reproduce or extend [21]-[22].

In network and artificial-intelligence research, datasets may originate from real-world measurements, such as UAV flight experiments and onboard network logs or from simulation-based environments using tools like NS-3 or OMNeT++, which allow controlled, parameterizable and repeatable experimentation. For FANETs, where real-world testing remains costly and technically challenging, simulation-based datasets represent an essential first step and can later be complemented by real-flight measurements to improve model generalization. From an AI and machine-learning perspective, the availability and quality of datasets directly affect model training, evaluation and generalization, as they provide the ground truth required for intelligent routing, QoS prediction (e.g., delay, packet-delivery ratio and energy consumption), failure detection and the design of mobility-aware and energy-efficient communication strategies. Without shared datasets, researchers are forced to repeatedly recreate similar experimental environments, resulting in poor reproducibility and inconsistent benchmarking, which ultimately hinder progress in AIdriven FANET research. In this context, datasets play a central role in the research cycle of intelligent FANET systems, serving as the foundation for data analysis, model development, performance evaluation and the continuous improvement of routing and communication protocols.

In summary, artificial-intelligence methods can be broadly divided into two categories: data-driven approaches, such as supervised and unsupervised learning and interaction-based approaches, such as reinforcement learning [24]. Data-driven approaches are the most widely used due to their strong performance; however, their effectiveness depends on the availability of high-quality datasets. This is precisely the gap that the present work addresses by providing a realistic, reproducible FANET communication dataset.

4. The Proposed FANET Dataset

After discussing the general motivation and scientific significance of datasets in AI and networking research, this section focuses specifically on the proposed dataset entitled "FANET Dataset: UAV Communication Scenarios in NS-3.40". This dataset has been designed to provide a reproducible, structured and extensible resource for analyzing UAV communication behavior, energy evolution and QoS under diverse operating conditions. The following sub-sections describe in detail its structure, content and organization. The dataset is publicly available and can be accessed and downloaded from Zenodo using the DOI: https://doi.org/10.5281/zenodo.19373220.

4.1 FANET Network Architecture

In all scenarios of the proposed dataset, the network follows a unified architecture composed of a fixed base station and multiple UAV nodes operating within a bounded three-dimensional area (in our case, $1000 \text{ m} \times 1000 \text{ m} \times 200 \text{ m}$). Thus, when a scenario specifies a total node count, for example 11 nodes, this corresponds to 10 UAVs plus one base station. Figure 1 provides an illustrative overview of the architecture used throughout the dataset generation. The communication model supports three interaction types, each reflecting a distinct operational paradigm in FANET environments:

UAV-to-UAV (U2U): Communication occurs exclusively between UAVs. The base station plays a negligible role in this mode. This configuration is relevant in applications where the base station is distant or inaccessible, such as military operations or remote-area missions.

UAV-to-Base-Station (U2B): UAVs communicate directly with the base station whenever possible. However, UAVs located too far from the base station may rely on multi-hop relaying through other

UAVs to reach it. This mode represents centralized monitoring, control or data-collection scenarios.

Mixed Communication (Hybrid Mode): UAVs communicate both among themselves and with the base station. This hybrid mode corresponds to collaborative missions where UAVs coordinate locally while also transmitting situational data to a central controller.

This architectural framework ensures that the dataset captures realistic communication patterns encountered in modern FANET deployments, supporting diverse routing behaviors, mobility constraints and QoS conditions.

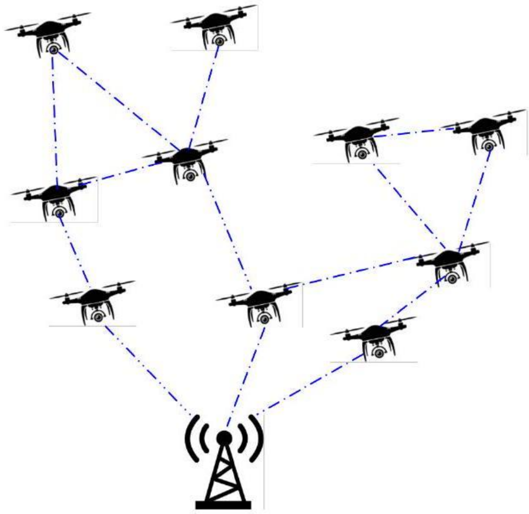

Figure 1. FANET network architecture (Example of 11 nodes, one base station and 10 drones).

4.2 Overview of Dataset Design

The FANET Dataset: UAV Communication Scenarios in NS-3.40 has been designed to provide a comprehensive, reproducible and structured source of data describing the behavior of UAV nodes operating in FANETs. The dataset captures mobility dynamics, energy consumption, routing activity and QoS metrics in various 3D network configurations. It serves as a benchmark for researchers working on routing optimization, QoS-aware communication and AI-based approaches for FANETs.

The dataset includes eight distinct simulation scenarios, each representing a specific combination of UAV density, speed, communication type and energy level. By systematically varying these parameters, the dataset provides a diverse and balanced representation of network behaviors under different environmental and operational conditions.

4.3 Scenario Structure (S1-S8)

The eight scenarios (S1 to S8) cover a range of configurations that vary in node density, mobility speed, initial energy, transmission range, traffic type and communication architecture. Table 2 provides the parameter ranges used across scenarios, while Table 3 summarizes the specific configuration of each scenario. The scenarios span from relatively stable conditions (S1: low density, low speed, high range) to more challenging ones (S6, S7, S8: high density, high speed, low range), allowing researchers to study network behavior across different regimes.

Table 2. Parameter levels for the FANET dataset scenarios.

Parameter	Level	Description / Interval
Node Density	Low Medium High	11 nodes (1 base station + 10 UAVs) 31 nodes (1 base station +30 UAVs) 51 nodes (1 base station + 50 UAVs)
Speed	Low; Medium; High	10m/s; 15m/s; 20m/s
Initial Energy	Low; Medium; High	100-150 J; 150-200 J; 200-300 J
Transmission Range	Low; Medium; High	250 m; 350 m; 400 m
Traffic Type	-	CBR / Video

Table 3. Scenario configuration summary (S1-S8).

Sc.	Architecture	Density	Speed	Energy	Range	Traffic
S1	UAV ↔UAV	Low	Low	Low	High	CBR
S2	Mixed (UAV ↔ UAV + UAV → BS)	Low	Medium	Medium	High	Video
S3	UAV → BS	Medium	Medium	Medium	Medium	CBR
S4	Mixed (UAV ↔UAV + UAV →BS)	Medium	Low	Low	Low	CBR
S5	UAV ↔UAV	Medium	High	High	Medium	Video
S6	UAV ↔UAV	High	Low	Medium	Low	CBR
S7	Mixed (UAV ↔ UAV + UAV → BS)	High	Medium	High	Low	Video
S8	UAV → BS	High	High	Low	Low	CBR

4.4 Data Organization and File Descriptions

The FANET dataset is organized in a hierarchical structure to facilitate navigation, analysis and reproducibility. Each scenario (S1-S8) is stored in a separate directory containing all CSV (Comma-separated values) files documenting the simulation results. The root directory includes the main documentation and metadata files. This organization ensures that each scenario is self-contained and can be independently analyzed, reproduced or extended.

Table 4 summarizes the main dataset files and their contents.

Note on packet counters:

- packet_trace.csv: all packets (DATA + OLSR); multi-hop retransmissions appear as separate reception events.
- olsr_links.csv: only OLSR HELLO messages (broadcasts).
- network_qos_metrics.csv and node_qos_metrics.csv:
    - sent_pkts, recv_pkts, throughput: all packets.
    - goodput, avg_delay_ms, jitter_ms: only DATA packets at final destination.
    - PDR, ETX: only DATA packets.
    - "Sent" counter: original transmission only (intermediate hops not counted).
- node_state.csv, olsr_node_state.csv: not affected by packet counters.

In addition to the CSV files described above, the Zenodo repository contains the NS-3 simulation source files that were modified or created for this work, specifically FANET_Dataset.cc, olsr-routing-proto col.cc, olsr-routing-protocol.h, ipv4-13-protocol.cc and ipv4-13-protocol.h. These files, along with the standard NS-3.40 source code, allow researchers to fully reproduce the simulations. Python postprocessing scripts used to generate the final CSV outputs are also included. A README file provides instructions for compiling and running the simulations.

Table 4. Dataset files and descriptions.

File name	Description
packet_trace.csv	Contains all transmission and reception events for each packet, including timestamps, source and destination node IDs, RSSI, SNR and delay.
network_qos_metrics.csv	Aggregated QoS metrics at the network level, including throughput, jitter, delay, packet delivery ratio, loss rate and ETX.
node_qos_metrics.csv	Node-level QoS indicators showing per-node performance and communication efficiency.
node__state.csv	Describes each UAV's energy status, position, velocity and motion parameters during the simulation.
olsr_links.csv	Details of link distances and symmetry between neighboring UAVs.
olsr_node_state.csv	Routing information related to OLSR, including neighbor sets, MPR configurations and control message counts.
simulation_scenario.csv	Metadata describing the simulation configuration, such as density level, speed, energy, transmission range, traffic type and communication architecture.

4.5 Metrics and Parameters Captured

The dataset records multiple key metrics and parameters for each UAV and the network as a whole.

- Mobility parameters: 3D positions (X, Y, Z), velocities, yaw/pitch angles.
- Energy metrics: Initial energy, remaining energy, energy consumption over time.
- QoS metrics: Throughput, delay, jitter, packet delivery ratio, loss rate, ETX, goodput.
- Routing parameters: OLSR neighbor sets, MPR sets, hello/TC message counts, link symmetry.
- Traffic characteristics: Type (CBR/video), sent/received packets and bytes per node.

The following definitions clarify how the QoS metrics are computed.

Metric definitions:

- PDR (Packet Delivery Ratio) = DestinationRecvDataPkts / sent_data_pkts (DATA packets received at final destination / DATA packets sent by the sources)
- ETX (Expected Transmission Count) = sent_data_pkts / DestinationRecvDataPkts
- Throughput (bps) = (recv_bytes_all × 8)/ duration (all received packets, including OLSR)
- Goodput (bps) = (DestinationRecvDataBytes × 8)/ duration (only DATA bytes received at final destination)
- Jitter (ms) = standard deviation of Link_Delay_ms for DATA packets
- Loss Rate = 1 - PDR

4.6 Dataset Statistics

We ran eight simulation scenarios, each lasting 200 seconds. Table 5 gives a quick overview of what each scenario generated in terms of packet traffic and file sizes. For each scenario, we included the total number of packets sent and received, the resulting packet delivery ratio (PDR), how many active flows were present and how many rows you'll find in the main CSV files (packet traces, node states and OLSR links).

Table 5. Dataset summary statistics per scenario.

Scenario	Total Packets Sent	Total Packets Received	PDR (%)	Number of Active Flows	Packet Trace Rows	Node State Rows	OLSR Links Rows
S1	52478	42529	81.0	5	128266	3723	12339
S2	56546	32061	56.7	6	130628	4389	13875
S3	65233	24700	37.9	10	252455	12344	85961
S4	71559	35422	49.5	9	213739	10251	40042
S5	52038	28657	55.1	10	230119	12369	80120
S6	56258	17428	31.0	8	300184	19838	102302
S7	49867	19275	38.7	10	265616	20349	106344
S8	53849	24491	45.5	7	230545	14659	72593

Looking at the whole dataset, we end up with roughly 2.57 million rows spread across all CSV files. That breaks down to about 1.75 million packet-related events, 0.10 million entries recording node states and 0.51 million rows of OLSR link information. The total size of the dataset is around 250 MB.

4.7 Example of Recorded Variables

To illustrate the types of data captured in the FANET Dataset, we present excerpts from two representative files: network_qos_metrics.csv and packet_trace.csv. Table 6 shows aggregated QoS metrics over consecutive time windows, such as packet delivery ratio (PDR), expected transmission count (ETX) and average link delay. Table 7 gives a closer look at individual packet events, timestamps, source and destination nodes and signal-to-noise ratio (SNR), revealing the fine-grained behavior of UAV communications.

Table 6. Excerpt from network_qos_metrics.csv showing network-level QoS metrics over time windows.

Window Start (s)	Window End (s)	Sent (DATA)	Recv (DATA)	Avg Link Delay (ms)	ETX	PDR
51.0	54.0	1438	795	0.922	1.809	0.553
54.0	57.0	1335	892	1.019	1.497	0.668
57.0	60.0	1234	655	1.350	1.884	0.531
60.0	63.0	1420	1225	1.290	1.159	0.863
63.0	66.0	1260	1113	1.370	1.132	0.883

Table 7. Excerpt from packet_trace.csv showing per-packet transmission and reception events.

TxTime (s)	PacketUid	NodeIdTx	NodeIdDst	RxTime (s)	NodeIdRx	SNR (dB)
50.1216	8890	7	Broadcast	50.1219	9	17.70
50.1216	8890	7	Broadcast	50.1219	0	16.43
50.1511	8896	3	0	50.1517	0	13.68
50.1532	8896	0	8	50.1538	8	15.88
50.1500	8898	3	Broadcast	50.1502	1	28.60

5. Methodology and Simulation Environment

5.1 NS-3.40 Setup and Simulation Configuration

All simulation scenarios were implemented using the NS-3.40 network simulator. The simulation environment represents a three-dimensional space of $1000 \times 1000 \times 200$ meters, in which UAVs follow the Random Waypoint mobility model. Each scenario runs for 200 seconds, during which all events-such as packet transmissions, receptions and node states-are recorded in CSV files to ensure reproducibility.

Table 8 summarizes the fixed simulation parameters and protocol settings used across all scenarios.

Table 8. Fixed simulation parameters and protocol settings.

Category	Parameter	Value
Wireless / PHY	Wi-Fi standard Carrier frequency Channel width Propagation model Fading model Transmission power Receiver sensitivity MAC retry limit Queue size (per interface)	802.11b 2.4 GHz (default for 802.11b) 22 MHz (default for 802.11b) FriisPropagationLossModel None Varies per scenario (12.6-16.7 dBm) -90 dBm (default) 7 (default) 100 packets (default)
Traffic	CBR traffic Video traffic	Packet size = 512 bytes, CBR rate = 2Mbps VBR ($2-6$Mbps), packet size 1024 bytes, exponential on/off
Mobility	Mobility model Pause time Waypoint generation Altitude range Speed min/max	3D Random Waypoint 10 s Uniform random within simulation area ($0-1000$ m in X, $0-1000$ m in Y, $0-200$ m in Z) $0-200$ m As per scenario ($5-20$ m/s)
Simulation	Simulation duration Random seeds Number of repetitions	200 s Default ns-3 seeds (not explicitly set) 1 per scenario (no repeated runs)

5.2 Routing Protocol

We chose OLSR as the routing protocol across all scenarios. Its proactive nature means it keeps routing tables updated continuously rather than waiting for a route request-something we found useful in highly dynamic environments, like FANETs. The standard OLSR implementation in ns- 3 was used without modifying its internal logic. We did, however, adjust two timing parameters to better suit UAV mobility: the HELLO interval was lowered from 2s to 0.5 s and the TC interval from 5s to 1.5s. This allows neighbor detection and topology updates to happen more frequently, which is helpful when nodes move quickly in 3D space.

It's worth noting that the goal here isn't to evaluate OLSR itself or claim it's the best choice for FANETs. Instead, we use it as a stable baseline to collect rich data-mobility traces, link changes, neighbor relationships and routing events, like HELLO messages, MPR selections and TC updates-all saved in CSV format. Our hope is that the community can use this dataset to experiment with their own routing protocols, whether traditional, AI-based or QoS-aware, using realistic aerial mobility and communication traces.

5.3 Mobility and Energy Models

We modeled UAV mobility in three dimensions using the random waypoint model, with minimum and maximum speed variations (10, 15 and 20 m/s) according to scenario settings. Each UAV node includes an energy source (BasicEnergySource) and a radio energy model (WifiRadioEnergyModel) to simulate energy consumption for transmissions and receptions. Node positions, velocities orientations (yaw, pitch) and remaining energy are logged at each time step.

5.4 Parameter Space

The dataset explores a multi-dimensional parameter space to capture diverse network behaviors:

- **Node density:** Low (11 total nodes: 1 base station +10 UAVs), Medium (31 total nodes: 1 base station +30 UAVs), High (51 total nodes: 1 base station +50 UAVs)
- **Speed:** 10, 15, 20 m/s
- **Transmission range:** 250 m, 350 m, 400 m
- **Traffic type:** CBR and video streams
- **Communication types:** UAV ↔UAV, UAV → BS or Mixed

These parameters are systematically varied across the eight scenarios to ensure a comprehensive dataset for AI-based routing studies, QoS evaluation and energy-aware network analysis.

5.5 Experimental Reproducibility

To ensure reproducibility, all scenarios use explicitly defined random seeds for mobility and traffic generation. Simulation logs record every packet event, node state and QoS metric with time stamps. Scenariospecific configuration files document the parameter values, allowing any researcher to exactly reproduce a given simulation or extend it with additional UAVs or traffic conditions.

5.6 Dataset Construction Workflow

The proposed FANET dataset is generated through a multi-stage pipeline that combines physical-layer traces, routing-layer logs, node mobility and energy states and Python-based post-processing for QoS metric extraction. Each final CSV file included in the dataset corresponds to a specific layer or functional aspect of the FANET communication process.

Physical Layer Packet Traces: At the PHY layer, NS-3.40 is instrumented to record all transmission and reception events. Two raw data streams are produced:

- tx.csv: captures every transmission event (Phy/TxBegin), including transmission time, packet UID, transmitting node ID, power level, packet size and data rate.
- rx.csv: records each reception event (Phy/RxEnd), including reception time, receiving node ID, RSSI, noise, SNR and link delay.

These two sources are combined to create the final file:

- packet_trace.csv: a unified table linking each transmitted packet to its corresponding receptions. It includes PHY-layer metrics, such as RSSI, SNR, noise power, transmission power, link delay, packet type classification and sender/receiver roles.

This file represents the complete physical communication behavior of the FANET.

Routing Layer Traces (OLSR): The OLSR routing protocol is instrumented to extract protocol-level state evolution:

- olsr_links.csv: lists, for each node and each time step, its neighbor nodes, link symmetry status and inter-node distance.
- olsr_node_state.csv: records OLSR internal dynamics including MPR selection, one-hop and two-hop neighbor counts, HELLO and TC activity and MPR set evolution.

These files provide a protocol-centric perspective on network topology, stability and routing behavior.

Node Mobility, Energy and Traffic State: A separate trace provides detailed node-level evolution over time:

- node_state.csv: includes mobility information (3D position, velocity, speed, yaw, pitch), energy status (initial and remaining energy) and traffic parameters (data mode and data rate).

This file is essential for correlating communication performance with mobility patterns and energy constraints of UAVs.

QoS Metrics Generation via Python Post-processing: Python scripts process the raw physical and routing logs to compute network-wide and per-node performance metrics:

- network_qos_metrics.csv: aggregates global metrics over time windows, including sent and received packets/bytes, average delay, jitter, throughput, goodput, ETX, Packet Delivery Ratio (PDR) and packet loss rate.
- node_qos_metrics.csv: provides per-UAV QoS indicators, such as per-node throughput, delay, jitter, sent/received data, delivered data packets and goodput.

These tables enable fine-grained evaluation of performance at both local (node-level) and global (networklevel) scales.

Scenario Description: Finally, a scenario descriptor summarizes all configuration parameters:

- simulation_scenario.csv: defines density levels, mobility categories, energy configurations, communication range levels, traffic type, communication patterns (UAV-to-UAV, UAV-to-BS or mixed), number of source/destination UAVs, protocol (OLSR), total duration and simulation zone size.

Final Dataset Organization: All tables are generated with consistent timestamps, node identifiers and unified variable naming. Together, the dataset provides:

- physical-layer communication traces,
- routing-layer protocol dynamics,
- UAV mobility and energy evolution,
- QoS metrics at network and node levels,
- full scenario descriptors for reproducibility.

This multi-layer architecture offers a comprehensive view of FANET behavior across diverse configurations and enables cross-layer analysis for UAV communication research.

6. DATASET VALIDATION AND CONSISTENCY CHECKS

6.1 Data Verification

To ensure the reliability and scientific integrity of the FANET dataset, multiple validation and consistency checks were performed. Each CSV file was examined for:

- Missing values: All fields are verified to contain valid entries. For instance, packets that were not received are explicitly marked with NaN values in RxTime_s, NodeIdRx or RSSI.

- Consistency across runs: Metrics, such as total sent and received packets, node energy evolution and connectivity patterns, are compared across multiple simulation repetitions using different random seeds.
- Range validity: All parameters are checked against expected ranges (e.g., UAV speeds between 10-20 m/s, energy levels within initial configuration bounds, transmission power within radio model specifications).
- Protocol integrity: OLSR routing variables, such as neighbor sets, MPR selections and TC messages, are verified to align with network topology changes over time.

In addition to these internal checks, we examined how key QoS metrics evolve across the eight scenarios to verify that the dataset behaves consistently with expected network dynamics. Figure 3 shows the average Packet Delivery Ratio (PDR) and Figure 2 shows the average Expected Transmission Count (ETX) for each scenario, with error bars indicating the standard deviation over time. For these averages, windows without any DATA traffic were excluded to avoid biasing the metrics.

As expected, Scenario 1 (low mobility, high transmission range) achieves the highest PDR (0.848) and the lowest ETX (1.277), indicating very reliable communication. In contrast, Scenarios 6 and 7 (high node density, low transmission range) exhibit the lowest PDR (0.375 and 0.305) and the highest ETX (13.06 and 24.30), reflecting the increased link instability and congestion under challenging network conditions. Video traffic (Scenarios 2, 5 and 7) results in higher throughput, but lower goodput, due to the increased load, which is consistent with the behavior of real FANET deployments. These trends confirm that the dataset captures realistic and coherent performance variations across different operational conditions.

Together, these checks confirm that the dataset reflects physically plausible UAV behavior and network dynamics, making it well-suited for research applications, such as AI-based routing, QoS evaluation and energy-aware FANET protocol design.

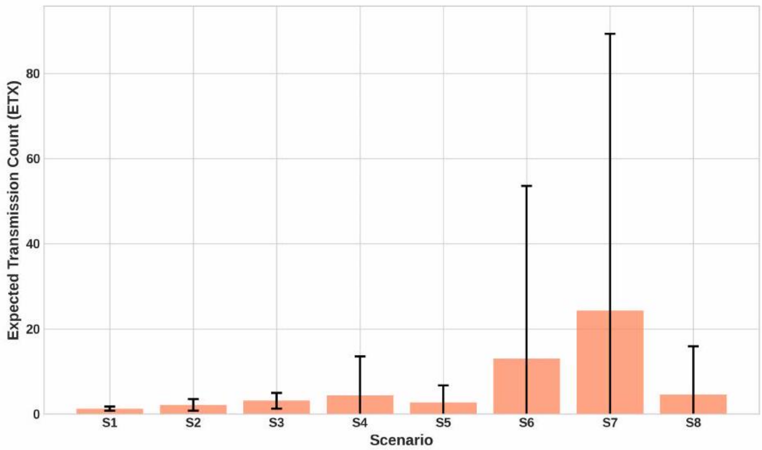

Figure 2. Average expected transmission count per scenario.

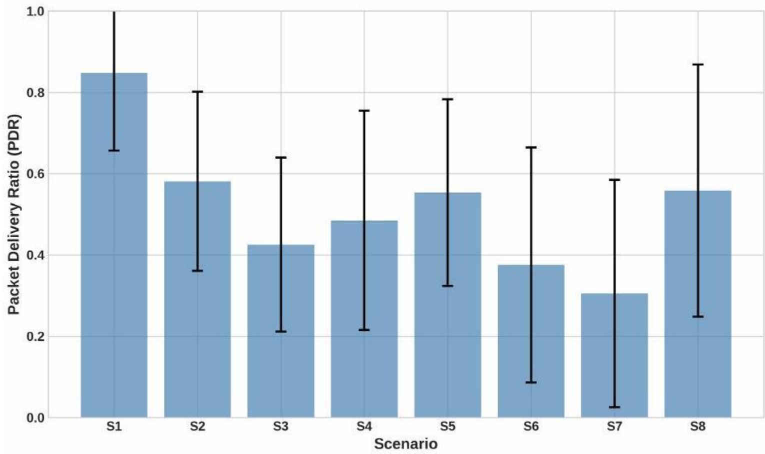

Figure 3. Average packet delivery ratio per scenario

6.2 Scientific Integrity

By systematically performing these checks, the dataset ensures:

- No internal contradictions between node-level and network-level metrics.
- Reproducibility across simulation runs.
- Accurate representation of UAV mobility, energy consumption and QoS performance.

These measures provide confidence that the dataset is suitable for research applications, including AIbased routing, QoS evaluation and energy-aware FANET protocol design.

7. Potential Applications and Research Impact

The FANET dataset offers a rich source of information that can support multiple research directions in UAV communication and networking. Its detailed recordings of node mobility, energy consumption, QoS metrics and protocol behavior enable the following applications:

7.1 AI-based Routing Model Training

The dataset provides labeled, time-stamped data suitable for training machine-learning and artificial-intelligence models aimed at routing optimization. Researchers can use node-level and network-level metrics to develop predictive or adaptive routing strategies that account for UAV mobility, link quality and energy constraints.

7.2 Quality of Service Optimization

Aggregated network QoS metrics, such as throughput, goodput, delay, jitter, PDR and ETX, allow for the evaluation and tuning of communication protocols. This facilitates the design of QoS-aware routing and scheduling strategies that ensure reliable UAV network performance under diverse operational conditions.

7.3 Energy-aware Communication Strategies

By capturing detailed energy consumption patterns of UAV nodes over time, the dataset enables the development of energy-efficient routing and transmission schemes. This is critical for extending UAV operational time and maintaining network connectivity in multi-UAV scenarios.

7.4 Topology Prediction and Link-stability Analysis

Recorded mobility and link-state information supports the study of dynamic-topology evolution. Researchers can analyze neighbor sets, MPR selection and link symmetry to predict network connectivity and link stability, which are essential for both protocol design and real-time network management.

7.5 Relevance across UAV, FANET, MANET and IoT Research

While focused on FANETs, the dataset provides insights applicable to broader networking contexts, including MANETs, VANETs and IoT-based UAV systems. Comparative studies across these domains are facilitated by the structured and reproducible nature of the dataset.

7.6 Benchmarking and Reproducible Research

The eight scenario configurations, with diverse densities, speeds, traffic types and energy levels, enable reproducible experiments and benchmarking of new algorithms. We didn't try to cover every possible combination; instead, we picked operating points that reflect realistic trade-offs across the main factors that affect network performance: density, mobility, transmission range, energy, traffic and architecture. The scenarios go from relatively easy conditions (S1: low density, low speed, high range) to much harder ones (S6, S7, S8: high density, high speed, low range). This lets researchers see how performance changes across different regimes without drowning in too many scenarios. Having multiple parameters vary at once is intentional, it pushes machine-learning models to learn how factors interact rather than just memorize isolated cases. If someone needs a different setup or wants to isolate a specific parameter, he/she can easily generate new scenarios using the simulation scripts we provide.

Researchers can replicate or extend scenarios to evaluate novel-routing, energy-management or QoS-optimization techniques in a controlled, realistic setting.

8. USAGE NOTES

The FANET dataset is designed to be easily accessible and reusable by the research community. The following instructions and recommendations support effective utilization:

8.1 Accessing the Dataset

The dataset is organized into eight scenario directories, each containing CSV files that describe node behavior, network QoS and simulation metadata. Users can download the dataset from the provided repository or Zenodo DOI, https://doi.org/10.5281/zenodo.19373220. The hierarchical structure ensures that each scenario can be independently analyzed or reproduced.

8.2 Recommended Pre-processing

Before using the dataset for analysis or modeling, we recommend the following pre-processing steps:

- Handle any missing or NaN values, especially in packet traces, using interpolation or filtering if required.
- Normalize or scale numeric variables, such as energy levels, throughput and delays, for machine-learning applications.
- Aggregate per-node or per-window metrics for comparative analysis across scenarios.
- Convert time units or synchronize timestamps if combining multiple scenario files for simulation-wide studies.
- For machine-learning experiments, avoid data leakage by splitting data appropriately. We recommend either using time-based splits (e.g., first 80% of timesteps for training, last 20% for testing) or splitting by simulation runs (e.g., train on a sub-set of scenarios, test on unseen ones).

8.3 Integration with Analysis Tools

The dataset is designed to be easily integrated into commonly used data analysis and simulation environments. It is fully compatible with standard scientific workflows and can be processed using widely adopted tools. In particular, Python-based environments allow efficient parsing, processing and visualization of the CSV files through libraries, such as pandas, NumPy and Matplotlib.

The dataset can also be imported into MATLAB using functions, such as readtable or csvread, enabling further modeling, statistical analysis and detailed evaluation of QoS metrics. In addition, the CSV output files can be reused within the NS-3 framework to validate custom simulation runs, reproduce the original scenarios or serve as input data for training and evaluating AI-based routing and optimization models.

8.4 Example Machine-learning Task

To illustrate how the dataset can be used for machine learning, consider predicting link delay (Link_Delay_ms) from physical-layer features. The packet_trace.csv file provides RSSI, noise, SNR and delay for each packet reception. A researcher could use these features to train a model that estimates delay from signal quality, useful for applications sensitive to latency.

For more advanced tasks, the dataset allows combining information from multiple files. For example, by joining packet_trace.csv (RSSI, noise, SNR, delay) with node_state.csv (remaining energy, velocity components) on node ID and timestamp, one can build a richer feature set that includes both link quality and node state. This enables predicting delay under varying mobility and energy conditions.

To further facilitate machine-learning experiments, the Zenodo repository includes an example_of_ml_ready folder containing pre-processed files for a sample task: link-stability prediction. Each scenario (S1 to S8) has a corresponding Link_Stability_For_ML_ScenarioX.csv file, built by joining olsr_links.csv, node_state.csv and packet_trace.csv. These files contain features, such as distance, signal quality (RSSI, SNR), node mobility (speed, velocity components), remaining energy and the label link_lifetime_s, which represents the estimated link durability. Researchers may use this pre-processed dataset directly to train models that predict link stability or they may define their own labels and feature sets from the raw CSV files.

These examples are just meant to show the dataset's flexibility, users can define their own prediction, classification or clustering tasks depending on their research goals.

8.5 Citation and License

Users are reminded to appropriately cite the dataset in any derivative work:

Ali, MOUSSAOUI; Hicham, Lakhlef (2026). FANET Dataset: UAV Communication Scenarios in NS-3.40. Zenodo. DOI: https://doi.org/10.5281/zenodo.19373220.

When the dataset or any derived version is used in a scientific work, this article should also be cited in addition to the dataset itself.

9. Conclusion and Future Perspectives

In this paper, we introduced a comprehensive dataset of UAV communication scenarios for FANETs, generated using the NS-3.40 simulator. Our dataset captures key aspects of FANET operation, including UAV mobility dynamics, energy consumption, QoS metrics and OLSR routing behavior across eight diverse simulation scenarios. By offering well-structured and fully reproducible data, the dataset provides a practical reference for researchers studying FANET performance, exploring routing optimization and developing AI-driven networking solutions. It also offers a solid data foundation for training and validating AI-based routing algorithms in three-dimensional UAV networks, while supporting reproducible experimentation and fair comparison across different FANET configurations.

A few clarifications are worth mentioning. The dataset relies on the 3D Random Waypoint mobility model and uses OLSR as the routing protocol. Both are standard choices that provide a reproducible baseline. The eight scenarios combine several parameters at once (density, speed, range, energy, traffic), which reflects the kind of trade-offs you would face in real deployments. We see these not as limitations, but as defining the scope of the current release. Since all simulation scripts are publicly available, other researchers can easily adapt the framework to include other mobility models, routing protocols or parameter setups if needed.

Looking ahead, we plan to extend the dataset in several directions. First, we will add more routing protocols, including AI-assisted approaches, to support broader benchmarking. Second, we aim to introduce more varied mobility patterns and eventually include data from real UAV flights. Third, we want to explore environmental effects and larger network scales to bring the simulations closer to real-world conditions.

Our goal is to keep enriching this resource so it can better support research on AI-driven, energy-aware communication strategies and help bridge the gap between simulation and real UAV deployments.

References

[1] I. Bekmezci, O. K. Sahingoz and Ş. Temel, "Flying Ad-hoc Networks (FANETs): A Survey," Ad Hoc Networks, vol. 11, no. 3, pp. 1254-1270, 2013.

[2] T. K. Bhatia et al., "Flying Ad-Hoc Networks (FANETs): A Review," EAI Endorsed Transactions on Energy Web, vol. 11, no. 10, 2024.

[3] A. Chriki et al., "FANET: Communication, Mobility Models and Security Issues," Computer Networks, vol. 163, p. 106877, 2019.

[4] F. Pasandideh et al., "A Review of Flying Ad Hoc Networks: Key Characteristics, Applications and Wireless Technologies," Remote Sensing, vol. 14, no. 18, p. 4459, 2022.

[5] O. S. Oubbati et al., "A Survey on Position-based Routing Protocols for Flying Ad Hoc Networks (FANETs)," Vehicular Communications, vol. 10, pp. 29-56, 2017.

[6] M. J. Almansor et al., "Routing Protocols Strategies for Flying Ad-Hoc Network (FANET): Review, Taxonomy and Open Research Issues," Alexandria Engineering Journal, vol. 109, pp. 553-577, 2024.

[7] C. A. T. Romero et al., "FANET and MANET, a Support and Composition Relationship," Computers, Materials Continua, vol. 82, no. 2, 2025.

[8] G. Amponis et al., "A Survey on FANET Routing from a Cross-layer Design Perspective," Journal of Systems Architecture, vol. 120, p. 102281, 2021.
[9] T. Clausen and P. Jacquet (eds.), "RFC 3626: Optimized Link State Routing Protocol (OLSR)," IETF, RFC Editor, United States, DOI: https://doi.org/10.17487/RFC3626, 2003.
[10] C. Perkins, E. Belding-Royer and S. Das, "RFC 3561: Ad Hoc On-demand Distance Vector (AODV) Routing," IETF, RFC Editor, United States, DOI: https://doi.org/10.17487/RFC3561, 2003.
[11] P. Khoshvaght et al., "Computational Intelligence-based Routing Schemes in Flying Ad-hoc Networks (FANETs): A Review," Vehicular Communications, vol. 53, p. 100913, 2025.
[12] M. Kaur et al., "Machine Learning-based Routing Protocol in Flying Ad Hoc Networks: A Review," Computers, Materials Continua, vol. 82, no. 2, 2025.
[13] C. Hutchins et al., "A Flying Ad-hoc Network Dataset for Early Time Series Classification of Grey Hole Attacks," Scientific Data, vol. 12, no. 1, p. 1431, 2025.
[14] Q. Zeng, A. Bashir and F. Nait-Abdesselam, "UAVIDS-2025: A Benchmark Dataset for Intrusion Detection in UAV Networks Using Machine Learning Techniques," Proc. of the 2025 IEEE Conf. on Comm. and Network Secur. (CNS), DOI: 10.1109/CNS66487.2025.11194990, Avignon, France, 2025.
[15] R. Rocha and A. Gradvohl, "Packet Time Delivery on Ad Hoc Network," [Online], Available: https://zenodo.org/record/817024, Version v1, 2012.
[16] S. Uppoor et al., "Generation and Analysis of a Large-scale Urban Vehicular Mobility Dataset," IEEE Transactions on Mobile Computing, vol. 13, no. 5, pp. 1061-1075, 2013.
[17] A. Mousaoui and H. Lakhlef, "FANET Dataset: UAV Communication Scenarios in NS-3.40," [Online], Available: https://doi.org/10.5281/zenodo.19373220, Version 2.0, 2026.
[18] T. Karunathilake, M. Zongo, D. Amarawardana and A. Förster, "CN+: Vehicular Dataset at Traffic Light Regulated Intersection in Bremen, Germany," Scientific Data, vol. 11, no. 1, p. 665, 2024.
[19] N. Akhtar, S. C. Ergen and O. Ozkasap, "Vehicle Mobility and Communication Channel Models for Realistic and Efficient Highway VANET Simulation," IEEE Transactions on Vehicular Technology, vol. 64, no. 1, pp. 248-262, 2014.
[20] R. W. Van Der Heijden, T. Lukaseder and F. Kargl, "VeReMi: A Dataset for Comparable Evaluation of Misbehavior Detection in VANETs," Proc. of the Int. Conf. on Security and Privacy in Communication Systems (SecureComm 2018), pp. 318-337, Cham: Springer International Publishing, 2018.
[21] A. Rovira-Sugranes et al., "A Review of AI-enabled Routing Protocols for UAV Networks: Trends, Challenges and Future Outlook," Ad Hoc Networks, vol. 130, p. 102790, 2022.
[22] S. Thirumuruganathan et al., "Data Curation with Deep Learning," Proc. of the 23rd Int. Conf. on Extending Database Technology (EDBT), pp. 277-286, DOI: 10.5441/002/edbt.2020.25, 2020.
[23] V. Singh et al., "A-Geo: Adaptive Geographic Routing for Consumer FANETs in Next-generation Communication," IEEE Transactions on Consumer Electronics, vol. 71, no. 4, pp. 11034-11043, 2025.
[24] K. Lv et al., "Large Language Model-empowered Energy-efficient Multi-UAV-Assisted MEC Heterogeneous Networks," IEEE Transactions on Cognitive Communications and Networking, vol. 12, pp. 5281-5294, 2025.

ملخص البحث:

تمكّن شبكات الطّائرات بدون طيار من التّواصل بين الطّائرات بدون طيار في بيئاتٍ شديدة الديناميكية تفتقر إلى البنية التّحتية. ومع ذلك، فإنّ الحركة العالية، ومحدودية الطّاقة المخزّنة، والتّغير السّريع في بنية الشّبكة تجعل من ضمان موثوقية الاتّصال وجودة الخدمة تحدّياً كبيراً.

تقدم هذه الورقة مجموعة بياناتٍ متاحة للعموم لشبكات الطّائرات بدون طيار تمّ إنشاؤها من خلال محاكاة تفصيلية باستخدام برنامج (NS-3.40)، وتتكوّن من ثمانية سيناريوهات اتّصال تتغير فيها كثافة العُقد، وسرعة الحركة، ومدى الإرسال، ومستويات الطّاقة، ونوع حركة البيانات، وبنية الاتّصال لكلّ سيناريو. وقد صُمّمت مجموعة البيانات لدعم تحليل الأداء، وقياس أداء البروتوكولات، وتطوير استراتيجيات توجيه مُراعية للطّاقة ومعتمدة على الذّكاء الاصطناعي. وهي تهدف إلى تسهيل إجراء تجارب قابلة للتّكرار، وتوفير مرجعٍ علمي عملي للبحوث المستقبلية في مجال شبكات اتّصالات الطّائرات بدون طيار.