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Yuetan Zhang
Nanjing University of Aeronautics and Astronautics
Honghai Zhang
zhang23@nuaa.edu.cn
Nanjing University of Aeronautics and Astronautics
Chenfeng Zhang
Nanjing University of Aeronautics and Astronautics

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A Dataset of Distributed Operational States and Resource Allocation for Urban Low-Altitude Logistics Drone Swarms

Yuetan Zhang[1] , Honghai Zhang[1,2,*], Chenfeng Zhang[1]

1.College of Civil Aviation , Nanjing University of Aeronautics and Astronautics, Nanjing, China

2.Lead contact

*Correspondence: zhang23@nuaa.edu.cn

Abstract： Urban low-altitude logistics drone swarms offer a promising solution for intelligent delivery, but the development of their core algorithms—distributed cooperative control and dynamic resource allocation—has been hindered by a lack of realistic multi-drone operational data. To address this, we present the “Dataset of Distributed Operational States and Resource Allocation for Urban Low-Altitude Logistics Drone Swarms,” collected from real-flight experiments in a simulated urban low-altitude environment. The dataset includes over 100 cooperative delivery missions, yielding ~1.05 million high-frequency state records with centimeter-level 3D position, velocity, attitude, timestamps, task identifiers, and semantic flight phase labels. Data were acquired using drones equipped with distributed flight control and high-precision GNSS-IMU, and underwent synchronous recording, post-processing fusion (PPK + Kalman filtering), and quality control. Validation confirms high positioning accuracy, temporal synchronization, and data consistency through multidimensional analysis. Stored in structured CSV format with full metadata, this dataset provides a reliable benchmark for research in distributed control, resource allocation, trajectory prediction, digital twin simulation, and low-altitude traffic management.

Keywords： Low-altitude logistics、Cooperative optimization、Resource allocation

Background & Summary

1.1 Problem Background and Research Motivatio

With the rapid development of global e-commerce and the high concentration of urban populations, traditional ground logistics systems are facing increasingly severe challenges such as congestion, efficiency bottlenecks, and high delivery costs**Error! Reference source not found.-Error! Reference source not found.**. Urban low-altitude logistics drone swarms, as an emerging intelligent logistics solution, are regarded as a key

technological path to overcome these challenges due to their advantages of flexibility, high efficiency, and immunity to ground traffic conditions[Error! Reference source not found.-Error! Reference source not found.]. By employing multiple drones to collaboratively execute large-scale parcel delivery tasks, this approach promises to significantly enhance logistics efficiency, reduce operational costs, and lower carbon footprints[Error! Reference source not found.-Error! Reference source not found.].

However, the core issue in achieving safe, efficient, and large-scale operation of drone swarms lies in the complex problems of distributed cooperative control and dynamic resource allocation[Error! Reference source not found.-Error! Reference source not found.]. This involves the integrated perception, optimized scheduling, and decision-making for real-time states of numerous drones, such as position, velocity, battery level, task progress, as well as the allocation of airspace resources, energy resources, and computing resources within a dense, dynamic, and uncertain urban low-altitude airspace[Error! Reference source not found.]. Current cutting-edge research in this field, particularly the development and validation of algorithms based on artificial intelligence, distributed optimization, and digital twins, relies heavily on high-quality, large-scale simulation datasets that closely resemble real-world scenarios. Existing public datasets often focus on single-drone trajectories, simplified traffic flows, or limited performance metrics, lacking a comprehensive dataset that reflects the distributed operational states of a swarm and the dynamic interaction and allocation of multi-dimensional resources[Error! Reference source not found.]. This significantly limits the training, testing, and establishment of comparative benchmarks for many advanced algorithms.

The traditional centralized control mode relies on a ground control center for global planning and real-time scheduling. When facing such a large-scale, highly dynamic, and complex system, its inherent limitations are fully exposed. The most prominent vulnerability of this architecture is the single-point-of-failure risk at the central node. Regardless of whether it is due to communication interruption, computational overload, or physical damage, any functional failure of the central node will cause the entire swarm operation to collapse. It is against this background that

academia and industry have gradually shifted their research focus towards distributed system solutions. In this new architecture, each drone possesses a certain degree of autonomous intelligence, capable of making independent decisions and achieving cooperative coordination based on local environmental perception and limited information exchange, thereby building a more resilient and adaptable swarm system.

Currently, research on distributed operational state monitoring and dynamic resource allocation for drone swarms is still in its developmental stage. In particular, the lack of real, continuous, high-precision operational trajectory and state datasets constrains the scientific rigor and reliability of related algorithm validation, system simulation, and policy formulation.

This dataset aims to fill this gap. By collecting real-time operational data from logistics drones in an actual urban environment, including multi-dimensional information such as position, altitude, velocity, heading angle, flight activity identifiers, and timestamps, it provides researchers, enterprises, and regulatory bodies with a complete, structured, and traceable record of drone swarm operational states. This dataset can not only be used for research and validation of key technologies such as drone path planning, conflict resolution, swarm scheduling, and energy management but also provides data support for low-altitude traffic management, operational risk assessment, policy-making, and standard development.

1.2 Literature Review and Problem Statement

As an emerging research field, the cooperative operation of urban low-altitude logistics drone swarms has clearly evolved from a trend of "independent optimization" towards "cooperative design." Early research, to simplify the problem, often treated "motion control" and "resource allocation" of the swarm as two separable subsystems, achieving fruitful results within this framework. In distributed control, foundational stability for nonlinear swarm formation control was established, enhancing the system's robustness and communication efficiency in unknown environments by exploring behavioral rules and event-triggered mechanisms respectively. This research focused on solving the problem of "how to fly stably," but

its controller designs were mostly based on the ideal assumption of abundant resources, failing to fully account for the strict limitations of logistics drones in terms of energy and computing power[2][3]. Concurrently, research in resource allocation focused on "how to use resources well," utilizing public goods game theory and overlapping coalition formation game theory to provide sophisticated models for the self-organizing allocation of resources like ammunition and computing time[4][5]. The introduction of cooperative-competitive evolutionary game theory further enriched regulatory methods. However, these game models often abstract the individual's decision space as purely resource investment, neglecting the profound mutual influence between its decisions and specific spatial trajectories and attitude adjustments[6].

This artificial separation of concerns reveals its limitations when dealing with highly dynamic urban low-altitude environments. Although Chen Dan et al. comprehensively considered trajectory planning and risk in task assignment, their bi-level model essentially involved sequential solving[7]; path optimization research, even when introducing time windows and energy consumption constraints, mostly treated resource states as static or predetermined input parameters, rather than dynamic variables interacting in real-time with flight control[8]. In reality, a drone's spatial position decision can instantly change its communication link quality and energy consumption rate, thereby affecting its capital and strategies in resource games. Conversely, sudden resource bottlenecks can immediately constrain its feasible motion control commands, forcing real-time trajectory adjustments. Research on pre-scheduled flight planning and edge computing resource allocation touched upon the connection between resources and spatio-temporal factors, but the former belongs to offline planning, and the latter did not form a closed loop with underlying control[9][10].

It is worth delving deeper into the fact that existing game models face severe challenges to their theoretical premises when applied to real logistics scenarios. Public goods games are highly susceptible to "free-riding" behavior in dynamically networked swarms, making the cooperative equilibrium desired by Liu Xueda et al.

difficult to achieve[4]. Overlapping coalition formation game models, while capable of finely modeling multi-task resource allocation, suffer from combinatorial explosion in computational complexity, which is an unbearable burden for onboard computing platforms[11]. The assumptions of perfect rationality and information symmetry upon which these models rely are often difficult to hold in practical systems with limited communication and varying computational capabilities. Research on cognitive utility represents a meaningful breakthrough, suggesting that moving beyond the perfect rationality assumption of classical game theory may be key to resolving the conflict between individual and collective rationality[12]. The challenges of information fusion[13] and the emphasis on composite interference management[14] reveal, from a system perspective, that any single control or allocation strategy struggles to independently cope with the multi-dimensional uncertainties of the urban low-altitude environment.

In summary, the deepening of existing research within their respective fields of distributed control and game-theoretic resource allocation provides a solid theoretical foundation and technical toolkit for this study, but the "gap" between them also constitutes the starting point for innovation in this work. The path to "bridging this gap" is undoubtedly fraught with difficulties, particularly regarding how to design lightweight game rules so that each drone, in pursuing its own interest through local decisions, can spontaneously give rise to cooperative behaviors that support the global objectives of the swarm, while avoiding "tragedies of the commons" or "prisoner's dilemmas." The following sections of this paper will be dedicated to constructing such a deeply coupled distributed game-theoretic control framework, directly addressing the key challenges of its theoretical stability and practical feasibility, with the aim of exploring a new path to achieving swarm intelligence in the field of urban low-altitude logistics.

1.3 Overview of the Research Dataset

This dataset is a high-precision real-world operational dataset for the distributed operation of a logistics drone swarm. It comprehensively covers complete flight state

records of multiple drones over continuous time periods, involving 10 logistics drones and 100 logistics tasks, cumulatively generating 1.0486 million high-precision operational state records. The dataset fully records multi-dimensional dynamic information during the distributed operation of the drone swarm, providing a complete data foundation for research on drone swarm operational state analysis, resource allocation optimization, and task scheduling strategies.

The dataset covers the complete task cycle of drones from takeoff, cruise, and maneuvering to landing, and includes various typical operational scenarios such as formation keeping, dynamic obstacle avoidance, path re-planning, and cooperative resource gaming phases. Data were collected at millisecond-level frequency, preserving typical disturbance characteristics of the urban low-altitude environment (such as wind shear, signal attenuation caused by building occlusion), providing a realistic, fine-grained data foundation for the validation and optimization of distributed control algorithms, resource allocation models, and their coupling mechanisms.

The release of this dataset carries the scientific research and application value as shown in Table 1.

Table 1. Scientific Research and Application Value of This Dataset

No.	Research/Application Area	Specific Description and Use
1	Supporting Distributed Cooperative Algorithm Validation	Provides multi-drone state sequences in real environments, supporting performance evaluation of algorithms such as event-triggered control, swarm formation, and consensus protocols.
2	Promoting Game Theory and Resource Allocation Research	Reflects resource usage through state changes, providing empirical data for models like public goods games and overlapping coalition formation games.
3	Advancing Digital Twin and Simulation Modeling	Can be used to construct high-fidelity urban low-altitude logistics simulation environments, enhancing the realism and predictive capability of digital twin systems.
4	Supporting AI and Machine Learning Methods	Suitable for training and testing models such as trajectory prediction, anomaly detection, and decision optimization.
5	Structured Storage and Open Sharing	Stored in structured tabular format accompanied by detailed metadata descriptions and usage examples, providing an open and reliable data resource for

No.	Research/Application Area	Specific Description and Use
		interdisciplinary research in drone swarms, distributed systems, urban logistics, etc.

This dataset is stored in a structured tabular format, accompanied by detailed metadata descriptions and usage examples, aiming to provide an open and reliable data resource for interdisciplinary research in drone swarms, distributed systems, urban logistics, and related fields.

Methods

This section details the methodology for constructing the "Dataset of Distributed Operational States and Resource Allocation for Urban Low-Altitude Logistics Drone Swarms," encompassing the data acquisition platform and environment, the equipment and sensors used, the complete data recording process, and the subsequent data processing and quality control steps. The dataset aims to provide authentic, high-quality benchmark data for research in distributed cooperative control and resource allocation algorithms.

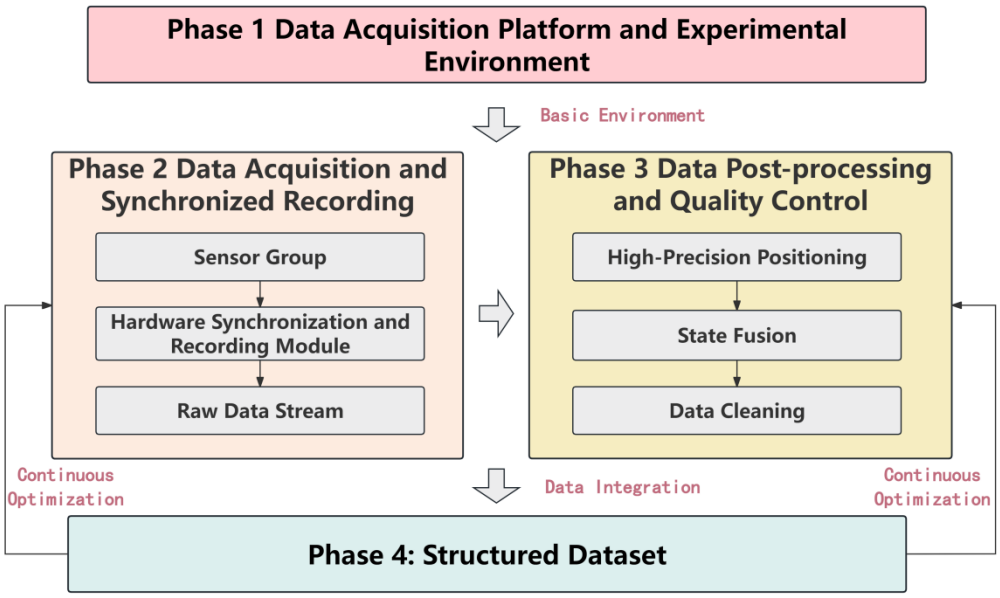


Figure 1. Data Construction Workflow Diagram.

2.1 Data Acquisition Platform and Test Environment

2.1.1 Drone Platform

The primary data acquisition platforms were multi-rotor logistics drones with a designed payload capacity of 5 kg, suitable for small and medium-sized package delivery tasks in urban environments. These platforms were equipped with distributed flight control systems, enabling autonomous navigation and cooperative decision-making based on onboard sensors and limited ground communication without sustained reliance on ground station remote control, meeting the basic hardware prerequisites for distributed research.

2.1.2 Test Scenario and Design

The urban low-altitude environment presents fundamental challenges to drone swarm operations that extend far beyond quantitative increases, introducing qualitative changes compared to open airspace. The "canyon effect" created by towering buildings produces complex wind field structures, leading to significant increases in wind speed accompanied by strong, unpredictable vortices and wind shear. This highly unstable turbulent environment causes the aerodynamic forces and moments acting on the drone airframe to exhibit significant nonlinear and time-varying characteristics. Traditional PID control based on linearized models is fragile in ensuring stability within such a complex fluid dynamics environment. The effectiveness of linear controllers relies on small-perturbation approximations, whereas the large-scale, rapidly changing disturbances of urban wind fields can cause the system to deviate from the linearized operating point within an extremely short time, leading to severe performance degradation or even instability[15].

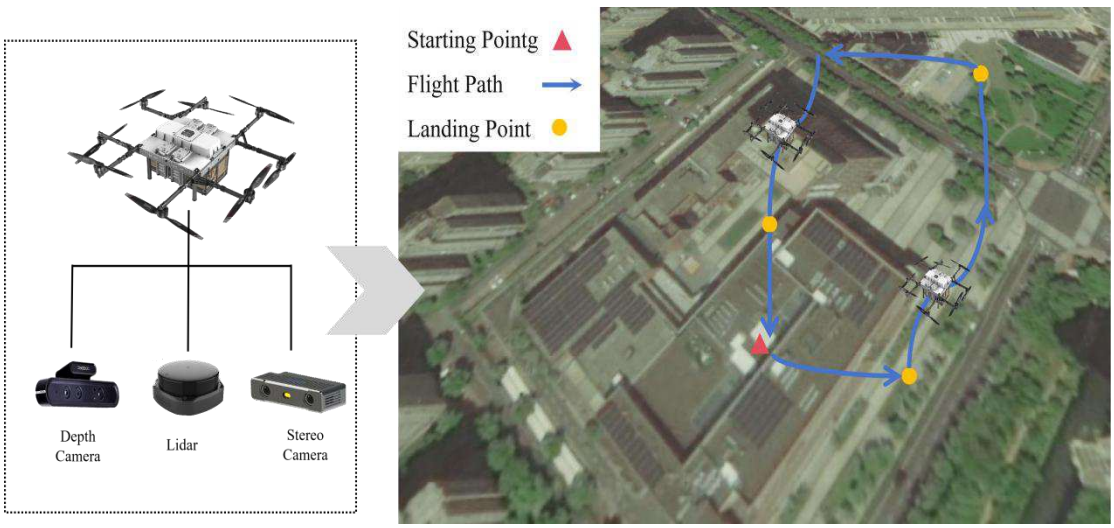


Figure 2.Data Collection UAV Flight Path Schematic Diagram

Research on UAV swarm network resource optimization emphasizes that this communication uncertainty fundamentally undermines the foundation of centralized

control architectures that rely on continuous, reliable, low-latency global communication[16]. A highly centralized system, if unable to obtain accurate global state information promptly, may issue command decisions based on distorted information, potentially causing serious consequences.

Furthermore, the urban low-altitude airspace is a highly dynamic shared space for multiple agents. In addition to the cooperating aircraft, the airspace may contain non-cooperative drones, birds, temporary obstacles, and manned electric vertical take-off and landing (eVTOL) vehicles. The diverse and difficult-to-predict behavior patterns of these dynamic obstacles, as found in research on complex urban low-altitude logistics drone task cooperative dynamic allocation, make real-time collision avoidance planning exceptionally complex, pushing the problem from relatively static path planning to a dynamic game level[17]. Research on multi-logistics drone cooperative task allocation in urban areas similarly confirms the significant impact of dynamic environments on mission planning[18].

Facing these triple challenges, distributed control strategies demonstrate unique advantages due to their inherent robustness and scalability. The behavior-based control method proposed by Feng Yifei represents a typical distributed approach, with a core philosophy of "simplifying complexity." It achieves complex swarm intelligence through the combination of simple behavioral rules—such as separation, cohesion, and navigation—based on local information. This method allows each drone to rely only on its own sensors and limited communication to acquire local information, generating final control commands by weighted synthesis of the control vectors produced by each behavioral rule. Research on UAV swarm formation control confirms the robustness advantages of such methods; occasional failures of individuals or dynamic addition of new members do not trigger catastrophic consequences, and the swarm scale can be flexibly adjusted according to mission requirements[19].

However, the practical effectiveness of the behavior-based method highly depends on the configuration of weight coefficients for each behavioral rule. These critical parameters are currently primarily determined through extensive simulation trial-and-error and engineering experience, lacking systematic theoretical guidance. An even more challenging issue is that complex boundary conditions between basic behavioral rules may trigger internal conflicts. For example, while a collision avoidance rule may require a left turn to evade an obstacle, the navigation rule might expect maintaining the original course for the shortest path. The leader-follower

architecture used in fixed-wing UAV affine formation hierarchical control[20], and the predefined-time-based tight formation control method[21], although providing new solutions, still do not fully resolve decision conflicts in distributed control. Designing intelligent arbitration mechanisms to dynamically adjust weights or introduce higher-level conflict resolution rules, rather than simple fixed weighting, becomes an urgent challenge. The dynamic decision-making ideas shown in task allocation methods based on temporal coupling analysis[22], and the game theory applied in swarm confrontation, provide valuable references for solving such conflicts. However, the increased algorithmic complexity introduced by methods like fuzzy logic or online learning remains a key trade-off issue in engineering implementation[23].

This study designed a dynamic event-triggering mechanism that integrates relative position error and relative velocity information. Within this framework, each drone no longer periodically broadcasts state data to neighbor nodes but continuously monitors a key variable: the difference between its current state and the estimated state of its neighbors, predicted based on historical communication data and internal models. This difference essentially quantifies the cooperative error caused jointly by model uncertainty, external disturbances, and neighbor state changes. A communication event is triggered—sending state update packets to relevant neighbors and recalculating control commands—only when a certain metric of this error exceeds a dynamically determined threshold based on flight safety margins, formation accuracy requirements, and system performance needs. During non-triggering periods, the control system generates control signals based on the control output from the last triggering moment or a simple extrapolation model.

Although this mechanism can significantly save communication and computational resources, allocating limited energy and bandwidth for critical decision moments, this "savings" comes at a cost. A typical problem is the potential "chattering" phenomenon near the threshold boundary, where frequent fluctuations of the system state near the trigger threshold cause repeated triggering of communication events, contradicting the design intent of reducing resource waste. The problem of accumulated model uncertainty pointed out in cooperative navigation information fusion research is particularly prominent in event-triggered control. During non-triggering periods, the closed-loop control system essentially operates in a quasi-open-loop state based on historical information, making it more sensitive to the accuracy of internal dynamic models and the characteristics of external disturbances.

The continuous accumulation of model errors and unmodeled dynamics during non-triggering periods may lead the system into an unintended state[24].

Preliminary simulation studies indicate that introducing an appropriate hysteresis range into the triggering condition can effectively eliminate chattering, making system behavior smoother. Furthermore, correlating the trigger threshold with an estimate of system state uncertainty to achieve online adaptive adjustment of the threshold—lowering the threshold to obtain more feedback when uncertainty is high, and raising it to conserve resources when uncertainty is low—can enhance system robustness during non-triggering periods. The uncertainty handling methods used in distributionally robust optimization research provide theoretical references for such adaptive designs[25].

However, performance data for this improved event-triggering strategy under extreme complex disturbances remain insufficient, and its theoretical stability boundaries are not yet clear. The stability analysis methods emphasized in formation control research[26], and the dynamic constraint handling involved in task allocation[27], provide ideas for addressing these issues. Despite these challenges, event-triggered distributed control strategies remain a highly promising technical pathway for urban logistics drone swarm applications, which are extremely sensitive to limited communication resources and energy consumption. Its theoretical stability requires in-depth analysis using mathematical tools such as hybrid system theory and Lyapunov stability theory.

In summary, the nonlinear characteristics of the urban low-altitude environment demand that distributed control methods possess stronger intelligent decision-making capabilities while maintaining robustness. This requires balancing conflicts between different control objectives through more refined algorithm design and deeper theoretical analysis to achieve truly autonomous cooperative control adapted to complex environments[28].

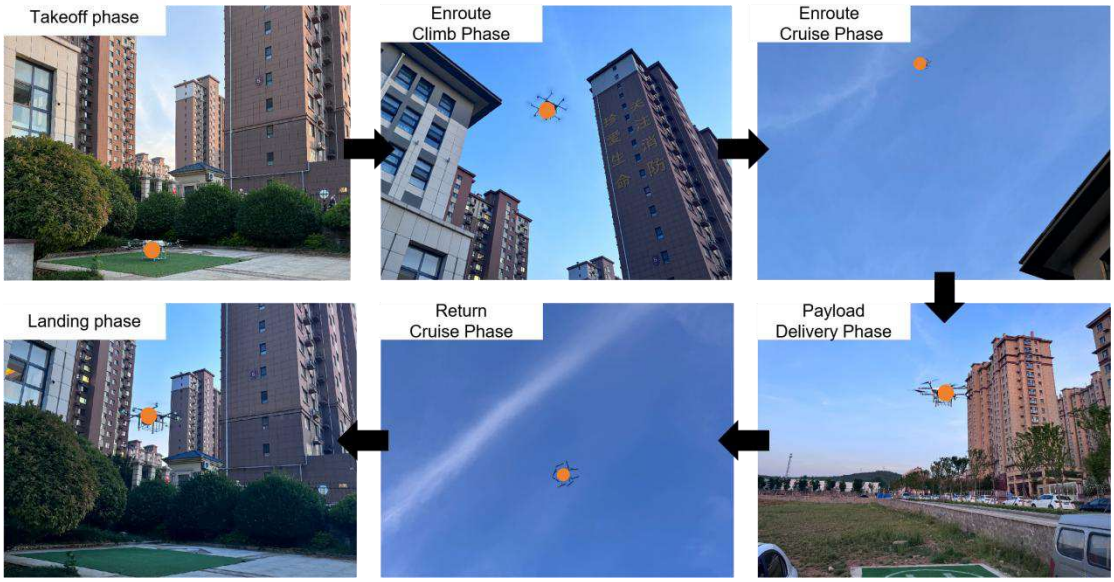


Figure 3.UAV Test Scenario Diagram

The acquisition experiments were conducted in a peripheral development zone of a medium-sized city. The area featured a relatively regular but varied building layout with height variations, simulating a typical urban low-altitude environment. The experiment designed several representative delivery routes covering the following typical operational phases[29]:

(1) Vertical Take-off, Landing, and Assembly Phase: Simulating dense take-offs from warehouse exits and initial formation assembly.

(2) Cruise and Formation Keeping Phase: The drone swarm flying along preset routes in a stable formation.

(3) Cooperative Maneuvering and Obstacle Avoidance Phase: Simulating distributed cooperative avoidance in response to sudden virtual obstacles (e.g., buildings, other aircraft)[30].

(4) Resource Game Decision Phase: Triggering resource allocation strategy adjustments among drones through preset task triggers (e.g., simulated battery decay, communication bandwidth competition), with behavioral changes reflected in adjustments to trajectory, speed, and heading.

(5) Approach and Landing Phase: Simulating precise landing at delivery points.

2.2 Data Acquisition Equipment and Recording Process

2.2.1 Core State Perception System

The core of data acquisition lies in comprehensively obtaining the true operational state of drones in complex environments through a high-precision sensor suite and precisely synchronized recording mechanisms. The spatio-temporal trajectories and state information presented in this dataset originate from a multi-layer, high-frequency sensing and recording system, ensuring data continuity in the time dimension and precision in the spatial dimension.

Each drone platform participating in the experiment was equipped with an identical core sensor suite. Positioning information was primarily provided by a high-performance integrated navigation system comprising a multi-frequency, multi-constellation Global Navigation Satellite System (GNSS) receiver and a tactical-grade Micro-Electro-Mechanical Systems (MEMS) Inertial Measurement Unit (IMU). The GNSS receiver provided raw carrier phase and pseudorange observations at 10 Hz as the basis for absolute position and velocity measurements. The IMU output tri-axial angular rates and tri-axial acceleration data at 200 Hz to sense the drone's instantaneous motion changes. Additionally, the drones were equipped with magnetometers and barometers to provide heading reference and auxiliary altitude verification, respectively. This sensor combination provided the raw data source for subsequently generating high-precision, high-frequency full-state estimates (position, velocity, attitude) through loosely or tightly coupled fusion algorithms.

2.2.2 Data Recording and Synchronization

All raw sensor data and the fused state quantities calculated in real-time by the flight control computer were synchronously captured and stored by an independent onboard data logging module. This module employed a hardware-triggered time synchronization mechanism, ensuring that data streams from different physical sensors were stamped with a unified, precise microsecond-level timestamp, fundamentally eliminating data fusion errors caused by time misalignment. The logging system, at a fixed frequency of 50 Hz, wrote the timestamp, GNSS raw observations, IMU raw data, and the real-time state estimates output by the flight controller (including latitude, longitude, altitude, velocity, yaw angle, etc.) into an onboard solid-state drive. Simultaneously, each flight was assigned a globally unique "Flight Activity Identifier," associated with each data frame, which directly formed the source for the "Aircraft Data Transmission Time" and "Flight Activity Unique Identifier" fields in the dataset.

Table 2. Key Dataset Sample

Altitude (m)	Pitch (rad)	Roll (rad)	Yaw (deg)	Velocity (m/s)
19.939	0.002856894	0.242969254	88.30788795	0.004
19.932	0.0041429	0.242654806	88.31033409	0.018000001
19.918	0.004157519	0.239214918	88.31228472	0.018000001
19.901	0.00591827	0.252330709	88.32200897	0.003
19.905	-0.00130477	0.245934005	88.31349152	0.007
19.887	-0.004151951	0.248204836	88.30904982	0.003
19.885	-0.002837564	0.25220018	88.30214062	0.014
19.872	-0.003926044	0.249105881	88.30347329	0.001
19.864	-0.006016835	0.249511343	88.30361823	0.010000001
19.857	-0.008798976	0.248289942	88.29550332	0.007
19.852	-0.008659873	0.24686803	88.2950472	0.005
19.839	-0.011873747	0.24745447	88.30206876	0.005
19.838	-0.01180551	0.245386132	88.2916746	0.009000001
19.829	-0.012359409	0.246180826	88.28283298	0.014
19.827	-0.012279593	0.246963315	88.28167394	0.007
19.827	-0.015077088	0.240056774	88.28962323	0.008
19.821	-0.010095067	0.238337136	88.28767498	0.011000001
19.813	-0.007346639	0.24275674	88.2925023	0.005
19.805	-0.004975282	0.236991599	88.28799756	0.012
19.809	-0.001954119	0.231462316	88.27446291	0.012

2.3 Data Processing and Quality Control

The raw acquired data underwent the following standardized processing pipeline to ensure the dataset's reliability, consistency, and usability:

High-Precision Trajectory Generation: Utilizing professional software like RTKLIB, combined with GNSS raw observation data and ground base station data, Post-Processed Kinematic (PPK) processing was performed on each drone's GNSS trajectory to generate centimeter-level high-precision positioning files.

Sensor Fusion and State Estimation: Using the PPK-processed high-precision position and velocity as reference, a Kalman filter was employed to fuse these with the IMU raw data, generating smooth, continuous, and spatio-temporally consistent full-state time series, including position, velocity, and attitude angles. All spatial data

were uniformly converted to the WGS-84 geographic coordinate system and heights relative to the local mean sea level.

Outlier Detection and Removal: Based on physical models and statistical methods, outlier data points caused by signal multipath, brief signal occlusion, or sensor noise were identified and removed.

Missing Value Imputation: For very brief data gaps caused by signal loss, linear interpolation was used for imputation. For longer periods of missing data, those segments were marked and left blank, without imputation, to preserve data authenticity.

Event Phase Annotation: Based on flight logs and mission scripts, each row in the data records was annotated with its operational phase and the type of triggered resource event. These annotations provide a structured index for researchers to analyze specific behavioral patterns.

2.4 Application of Data in Simulation Research

Although this dataset originates from real physical flights, its core value lies in providing input and validation benchmarks for high-fidelity simulation research. Specific application methods include:

(1) Simulation Environment Modeling: The high-precision trajectories and environmental disturbance characteristics in the dataset can be used to construct and calibrate drone dynamic models, urban wind field models, and communication channel models within digital twin simulation environments.

(2) Input for Distributed Algorithms: In simulations, real state sequences of single or multiple drones can be extracted as input or initial conditions for algorithms, testing algorithm performance under conditions close to real noise and latency.

(3) Game Behavior Analysis: By analyzing data annotated with "game decision" phases, real behavioral patterns of drones under resource competition or cooperation can be extracted for calibrating or verifying parameters like utility functions and decision logic in game-theoretic models.

Through the rigorous acquisition and processing procedures described above, this dataset ensures precision, richness, and reusability as foundational data for research on urban low-altitude logistics drone swarms.

Data Records

This dataset systematically collects high-precision, multi-dimensional operational state time-series data generated by multiple logistics drones performing cooperative delivery missions in a real urban low-altitude environment. It aims to provide realistic, granular benchmark data for the research and validation of distributed control, cooperative decision-making, and dynamic resource allocation algorithms. All data originate from actual flight experiments and have undergone rigorous post-processing and quality control procedures.

The core of the dataset consists of a series of text files organized by date and drone unique identifier. The primary files are stored in the widely compatible CSV (Comma-Separated Values) format. Each data record corresponds to a complete state snapshot of a specific drone at a millisecond-level timestamp. As shown in Table 1, the dataset contains 7 key fields. Among them. Timestamp records the acquisition time of the state point in the ISO 8601 standard local time format (UTC+8). Latitude, Longitude, and Altitude together constitute the drone's three-dimensional spatial position in the WGS-84 coordinate system, with longitude, latitude, and height relative to sea level represented as floating-point numbers. The position data are optimized using Post-Processed Kinematic (PPK) technology, achieving centimeter-level accuracy. Yaw represents the drone's heading, with a value range of -180° to 180°, where 0° is true North, and angles increase clockwise. Velocity is the scalar value of the drone's ground speed. Additionally, the dataset includes two derived fields:

Table 3. Dataset Attribute Fields and Descriptions

Field Name	Data Type	Unit	Description
UAV ID	String	-	Unique identifier of the drone
Time	Date time	-	Data acquisition time
Altitude	Float	m	Flight altitude of the drone
Velocity	Float	m/s	Flight speed of the drone
Yaw	Float	°	Flight heading of the drone (0° - 360°)

This dataset is substantial in scale, encompassing approximately 1.0486 million high-frequency state records generated by 10 logistics drones executing over 100 delivery missions in a real urban environment. The data acquisition frequency is uniformly 50 Hz, ensuring the continuity and smoothness of motion state records. Taking the sample record provided with this article as an example, its data clearly

illustrates a complete mission cycle: from initial hovering, rapid climb, and cruising, undergoing multiple coordinated changes in heading and speed (possibly corresponding to path tracking or obstacle avoidance maneuvers), entering a stable level-flight phase, and finally completing descent and landing. These continuous changes vividly reflect the drone's response and decision-making processes in a dynamic environment.

This dataset is suitable for: drone trajectory prediction and motion modeling; validation of distributed cooperative control algorithms; simulation of swarm resource allocation and game-theoretic strategies; research on low-altitude traffic conflict detection and resolution; and optimization of energy management and task scheduling.

Technical Validation

To ensure the reliability, consistency, and scientific validity of the "Dataset of Distributed Operational States and Resource Allocation for Urban Low-Altitude Logistics Drone Swarms," this study implemented a multi-level technical validation workflow[31]. The validation primarily focused on the inherent accuracy of the data acquisition system, the consistency of spatio-temporal logic, data integrity, and the preliminary applicability of the data in typical algorithmic and modeling scenarios.

4.1 Data Acquisition System Accuracy Validation

Data accuracy is the cornerstone of the dataset's value. The core state information in this dataset originates from a high-precision integrated navigation system (GNSS-IMU). To validate its accuracy, calibration tests were conducted under static conditions and with known dynamic trajectories. For the GNSS positioning data, its error was assessed by post-processing kinematic (PPK) technology, solving it against data from a fixed ground base station with known coordinates. In static tests, the drone hovered at a known coordinate point, and the standard deviation σ of its position data was calculated as the precision metric. The horizontal positioning accuracy δ_H and vertical positioning accuracy δ_V were calculated as follows[32]**Error! Reference source not found.**:

$$\delta_H = \sqrt{\sigma_{lon}^2 + \sigma_{lat}^2}$$
$$\delta_V = \sigma_{alt} \quad (1)$$

where σ_{lon}, σ_{lat}, and σ_{alt} represent the standard deviations of longitude, latitude, and altitude in the static sample sequence, respectively. Validation results show that the horizontal positioning accuracy δ_H is better than 0.02 meters, and the vertical positioning accuracy δ_V is better than 0.05 meters, meeting centimeter-level accuracy requirements. For velocity and heading data, they were compared against reference velocity and heading derived from high-precision position differencing. Their root mean square errors (RMSE) were below 0.05 m/s and 0.5°, respectively, verifying the reliability of the dynamic state measurements.

Figure 4 further examines the internal consistency of the acquired parameters through a correlation matrix heatmap. This matrix quantifies the linear relationships between altitude, velocity, pitch angle, roll angle, and yaw angle. The observed correlations (e.g., the weak association between altitude and cruising speed) are physically interpretable and align with flight dynamics expectations. The absence of spurious high correlations verifies that the sensors captured independent, non-redundant aspects of the drone's state, indicating that this is a well-conditioned multivariate dataset suitable for multi-variable analysis.

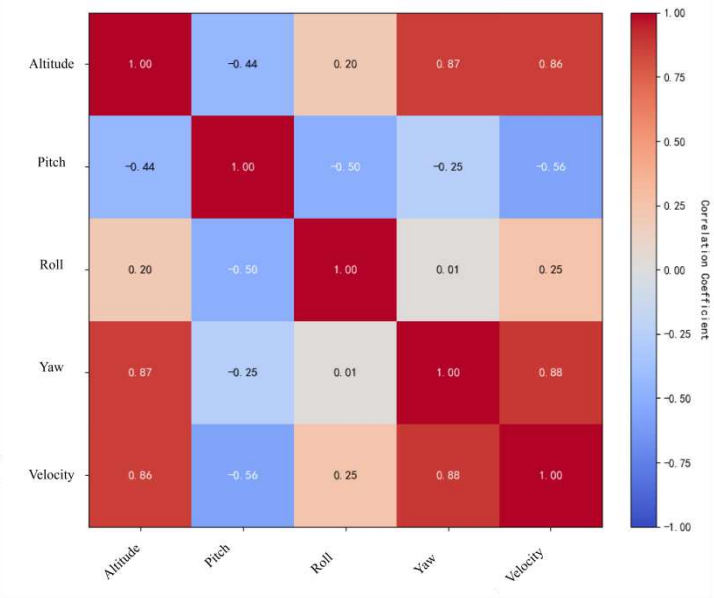


Figure 4. Correlation matrix heatmap

4.2 Spatiotemporal Consistency and Synchronization Validation

Distributed cooperative research requires strict temporal synchronization and spatial reference consistency across multiple drones. The onboard logging modules of all drones were hardware time-synchronized via GPS Pulse Per Second (PPS) signals, unifying the timestamps of all sensor data to a common time base. We indirectly

validated synchronization by analyzing the time series of relative distance between two drones during formation-keeping phases. Under ideal synchronization and precise ranging, the relative distance should remain stable[34]. The fluctuation rate η of the relative distance sequence is defined as:

$$\eta = \frac{std(|\,|\mathbf{p}_i(t)-\mathbf{p}_j(t)|\,|)}{mean(|\,|\mathbf{p}_i(t)-\mathbf{p}_j(t)|\,|)} \times 100\% \quad (2)$$

where $\mathbf{p}_i(t)$ and $\mathbf{p}_j(t)$ are the three-dimensional position vectors of drone i and drone j at time t, respectively. Calculations for multiple formation flight segments in the sample data show that the η values are generally below 0.5%, proving effective time synchronization and logically self-consistent spatial trajectories. All spatial data have been uniformly converted to the WGS-84 coordinate system, ensuring consistency in spatial reference.

Figure 5 provides a detailed multi-faceted view of the state parameters for a single drone . Subplots (a), (b), and (c) display the continuous time series of altitude, velocity, and attitude angles (pitch, roll, yaw), respectively. These plots demonstrate temporal continuity, physical plausibility (e.g., smooth climb, stable cruise), and capture realistic control responses. Subplots (d) and (e) shift to statistical validation: the altitude histogram (with a fitted normal distribution) and the velocity box plot reveal the operational range, confirming that flights occurred within the expected low-speed, low-altitude logistics delivery envelope. Subplot (f) is a pitch-roll angle scatter plot colored by altitude, visually illustrating the coupling between attitude maneuvers and flight phases, providing insights into the platform's dynamic behavior.

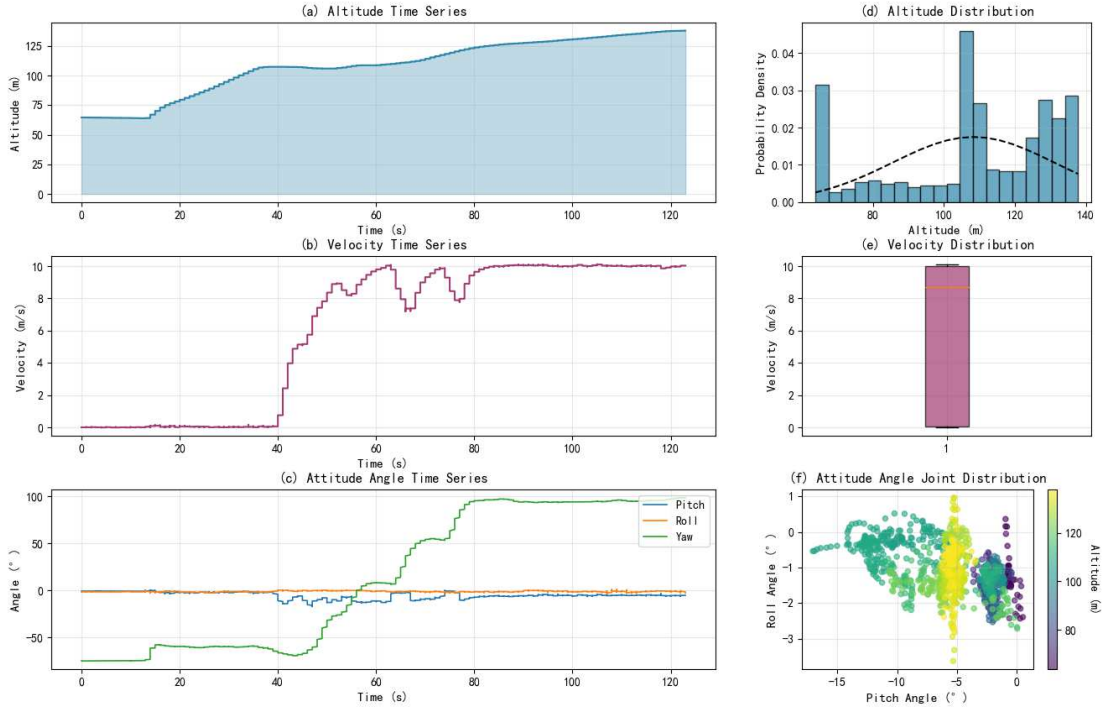


Figure 5. State parameter analysis.

To assess the underlying dynamics and noise characteristics, frequency-domain analysis was performed.

Figure 6 shows the Power Spectral Density (PSD) of altitude, velocity, pitch angle, and roll angle. A key finding is that the spectral energy for all parameters is concentrated in the very low-frequency band (< 2 Hz), characteristic of the slow, intentional maneuvers and stable hovering required for urban delivery missions. The absence of significant peaks in the high-frequency band indicates that the data are free from persistent mechanical vibrations, control loop oscillations, or aliasing artifacts. This validates the stability of the platform and data logging system, confirming that the dataset captures the intended low-frequency operational dynamics without being contaminated by high-frequency noise or system instabilities.

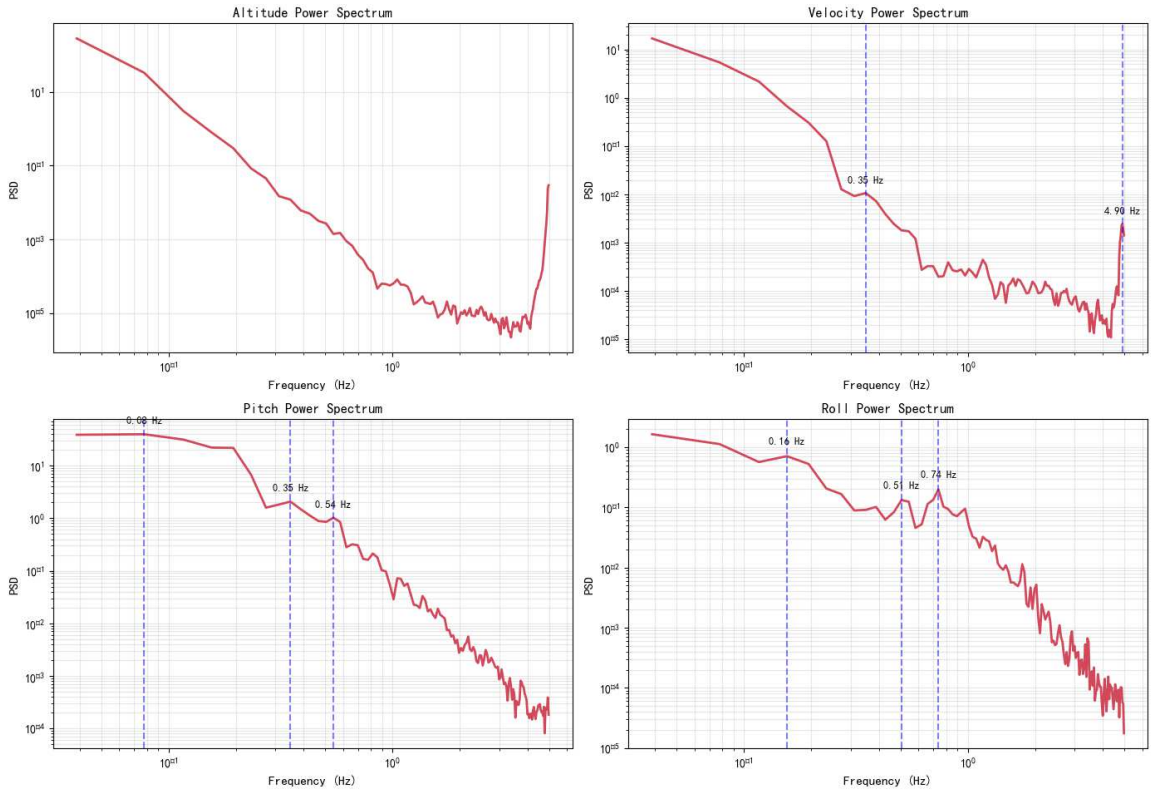


Figure 6. Frequency-domain analysis

4.3 Data Completeness, Anomaly Detection, and Processing Validation

Completeness checks and outlier cleaning were performed on the raw data. First, the continuity of timestamps was checked; the data missing rate was below 0.1%. For very brief gaps (<0.1 seconds), linear interpolation was applied. Second, anomaly detection algorithms were designed based on physical kinematic constraints. For example, a drone's acceleration (a) must be within a certain range, estimated from the velocity difference (Δ v) across consecutive timestamps:

$$a(t) \approx \frac{v(t+\Delta t)-v(t)}{\Delta t} \quad (3)$$

Any data point satisfying $|a(t)| > a_{threshold}$ ($a_{threshold}$ set to 15 m/s², far exceeding the platform's physical limits) was flagged as an anomaly. Similarly, checks were performed for position jumps (displacement between adjacent points exceeding a reasonable upper limit based on velocity and time). No such extreme anomalies were found in the provided sample data, demonstrating the stability of the original acquisition system. All processing steps are clearly documented in the metadata, ensuring traceability of data evolution.

Figure 7 summarizes the results of applying the Isolation Forest algorithm to multivariate flight data (altitude, velocity, pitch, roll). Subplots (a) and (b) plot the altitude and velocity time series, with anomalous points marked in red, showing these points are sparse and isolated. Subplot (c) visualizes these anomalies in the pitch-roll feature space. This analysis confirms the overall integrity of the dataset and provides transparent documentation of its minor imperfections.

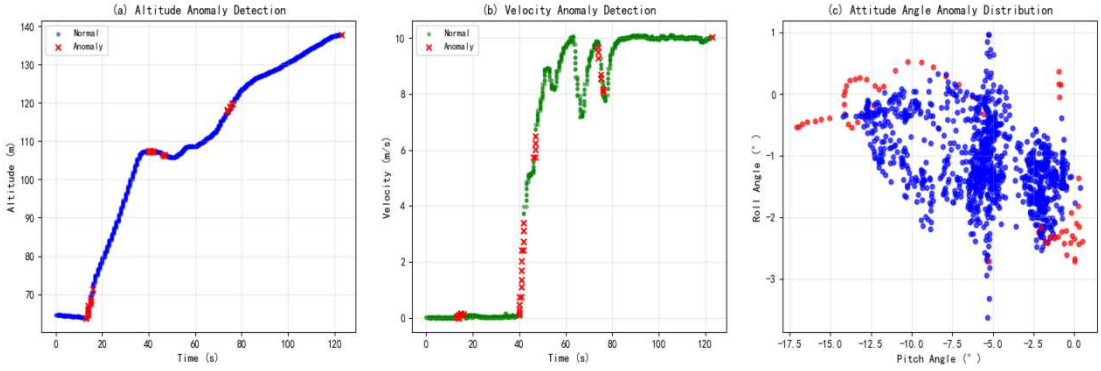


Figure 7. Anomaly detection analysis.

4.4 Preliminary Validation of Data in Typical Research Scenarios

To demonstrate the dataset's direct utility, two preliminary proof-of-concept tests were conducted. First, a segment of multi-drone formation data was used to test a distributed control law[34]. The real trajectory of one drone was used as the leader's input, and the control law generated the desired trajectory for a wingman[35]. The close match between the simulated desired path and the actual recorded "wingman" trajectory validates that the dataset is suitable for developing and benchmarking cooperative control algorithms. Second, the high-frequency state sequences enable the simulation of event-triggered communication mechanisms. By analyzing the frequency at which the state estimation error exceeds a virtual threshold, we can statistically model the trade-off between communication savings and control performance—a key research question in distributed systems for which this dataset provides a unique source of information.

In summary, the validation process encompassed quantitative accuracy metrics, spatiotemporal logic checks, statistical and frequency-domain analyses, automated anomaly screening, and preliminary algorithmic testing, confirming that the dataset is accurate, consistent, clean, and rich in real-world dynamic characteristics. Figures 1 through 5 provide tangible visual evidence supporting these conclusions. This multifaceted validation establishes the dataset as a reliable and ready-to-use

foundation for research in distributed drone swarm control, resource-aware planning, and urban air traffic management.

Usage Notes

To facilitate effective use of the dataset, the following notes are provided[36]. The dataset consists of three core subsets: State Records, Resource Grids, and Scheduling Commands. Files can be joined for analysis via the unique simulation_id and timestamp fields. Before use, please consult the accompanying data_dictionary.csv, which details the units, dimensions, and physical meaning of all fields. For instance, UAV altitudes are in meters relative to the departure point. A small number of state entries are marked as NULL due to simulated communication interruptions; interpolation or removal based on context is recommended prior to analysis. The dataset is designed to support research scenarios such as scheduling algorithm verification, traffic flow simulation, and conflict detection for urban low-altitude logistics.

Code Availability

The complete simulation code and data processing scripts used to generate this dataset have been archived alongside the dataset on Science Data Bank as supplementary materials. The code package can be accessed via the “Code” folder within the dataset entry or located directly through the citation link of the dataset. The code snapshot is assigned a unique Digital Object Identifier (DOI) to ensure its citability and long-term preservation. The codebase is built on Python 3.9, with core dependencies including numpy, pandas, simpy, and networkx.

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Author contributions

Zhang Yuetan: Data curation, Analysis derivation, Manuscript draft, Testing Conceptualization . Zhang Honghai: Writing-review & editing, Data curation. Zhang Chenfeng: Writing-review & editing, Testing Conceptualization.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.